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Can the Endogenization of Regimes Lead to Improved Forecasting of the UIP?

JONAS ANDERSSON[$] and ANDERS JOHANSSON[€]

ABSTRACT

Understanding exchange rate movements is key to making positive returns and good decisions when dealing with the currency markets. We try to increase that understanding by using a Markov switching approach to describe deviations from the Uncovered Interest rate Parity (UIP), before investigating what factors that are driving the transitions across regimes. We perform this analysis by endogenizing Markov states through a Logit model. We find that the transition between regimes can be explained by technical and fundamental indicators, especially for the chain which governs both the variance and the mean. Furthermore, we find strong support for the UIP, but that significant deviations caused by outside factors can exist during shorter time periods. Our out of sample statistics affirms better forecasts than a random walk, and our trading rule produces average net returns of 2.4% per annum.

Keywords: Exchange Rate, Forecasting, UIP, Markov Switching, Logit Regression

Tutor: Roméo Tédongap

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$ 19919@student.hhs.se

€ 20496@student.hhs.se

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1. Introduction

The general consensus in the previous literature (among others Schinasi and Swamy (1989), Brunnermeier et. al. (2009), Lyons and Rose (1995)) seems to be that the Uncovered Interest rate Parity (UIP) does not hold, but that it is hard to beat a random walk when trying to forecast those deviations. In this paper we look at previous work on the different areas within exchange rate modeling and forecasting to combine promising thoughts and results from both areas. Our main proposition is that the UIP deviations can be described by a non-linear process that is governed by some underlying exogenous fundamental and technical variables. Our hypothesis is that we can predict these non-linear processes by endogenizing the underlying regimes. By then running those values against the exogenous variables we examine if they can shed some light on the movements of exchange rates and thereby improve forecasts.

We will employ a non-linear Markov switching (MS) model where the first two orders of the UIP deviations are allowed to vary over time. The approach is more flexible than a linear alternative and should thereby provide a better fit to our sample data. As the Markov model is of explanatory character, we apply a Logit model to forecast the shifts between regimes themselves. Results are then used to simulate the exchange rate on our out of sample data and we set up a trading rule to measure the economical performance to complement the statistical tests made.

We use intraday exchange rate data on the nine most traded currencies against the US-dollar over the period of May 2000 to April 2010. We have also collected overnight interbank interest rates for the same period. Both the released figures and the analyst estimates for the fundamental indicators have been retrieved from Bloomberg.

The rest of the paper is organized as follows. First we will guide you through some selected literature in the area. We bring up issues such as why one might want to consider non-linear models, why the UIP is used, and how they can be combined in forecasting. Second, we present the data and descriptive statistics together with variable definition. Third, we explain the method in where we set up the non-linear estimation model and regime forecasting model. Fourth, we present our estimation results in the methodology part before we analyze that data and highlight issues in the following two sections. Finally, conclusions are drawn before a final general discussion.

2. Previous research

Meese and Rogoff (1983) were among the first in the literature to show that, especially at shorter horizons, a random walk forecast of the exchange rate generally outperforms alternative models drawn from economic theory, including Purchasing Power Parity (PPP), UIP and other models. The authors conclude this from running linear regressions on exchange rate data, but also add that the poor out-of-sample performance might be due to, among other issues, model misspecification.

Schinasi and Swamy (1989) argue that a better way to specify the Meese and Rogoff model is by using non-linear parameter estimation. By doing so they conclude that other variables than interest rates can be used in exchange rate modeling and that the UIP does not hold. They argue that the reason exchange rates need models where the coefficients are allowed to change is due to that 1) there is no reason for people to react the same to news during the different regimes, and 2) that the behavioral parameters should simply not be fixed over time.

Other papers have investigated the UIP deviations and come up with various explanations for this anomaly. For instance, historical data shows that high yielding currencies tend to appreciate, not depreciate which the UIP would predict. Brunnermeier et al. (2009) explains that this anomaly is commonly known as the forward premium puzzle. Lyons and Rose (1995) argue that the deviation from the UIP could be comparable to some sort of risk premium which stems from the risk of devaluation while holding the currency. This premium would then be positive in trades where a riskier currency is bought, and negative for safer currencies. Safer currencies are also known as safe haven currencies, as stated in Kaul and Sapp (2006) who furthermore explain that as a flight to these safe have currencies happen as markets become more uneasy. Additionally, Chaboud and Wright (2005) argue in their paper that this risk premium is the ex ante expected profit form a carry trade, which is when money is borrowed (sold) from a country with a low interest rate to buy a currency with a higher interest rate. However, we see that this anomaly does not seem to exist only in currencies with large interest rate spreads, but in many other currencies as well. This might be why numerous authors have tried to predict what is driving this general anomaly from the UIP.

Many papers have used Markov Switching (MS) models in their quest to assess the non-linearities in asset-pricing behavior. Guidolin et al. (2009) find that non-linear effects might be key to improve forecasting, and that specifically the MS model was the best among several models to use when modeling US and UK stock returns. The authors also argue, however, that while it is almost a general consensus that non-linear models do provide a richer understanding of the in-sample variable of interest, there is less evidence that MS models could be used successfully in forecasting applications.

Despite their economic appeal, MS models are less attractive than one-regime models from an econometric estimation perspective. Although with the recent work of Gray (1996) and Hamilton (1994) the likelihood construction has been simplified, estimating MS models is still not trivial, and needs a numerical approach for the solution. Ang and Bekaertz (2002a) furthermore conclude that the MS model is less accurate in out-of-sample data. It is argued that this problem could stem from the Peso problem, in which the fraction of observations drawn from a particular regime in the sample at hand may not correspond to the true population frequency of that regime. Clements and Francis (2003) also warn against the expectation that MS models will always do well even in sample. They argue that the economic system is too complex to generalize it with simply another dimension, such as adding another regime to the equation, and that it will not necessarily improve anything. However, the authors support the use of non-linear models, arguing that if the underlying relationship is non-linear, it is worth considering a non-linear model.

Engel (1994) concluded that MS models tend to fit in sample data better than linear models and they also find that quarterly data fit better than monthly data in sample predictions. However, the out of sample forecasts still do not seem to be able to beat a random walk. Assuming that each forecast the random walk predicts is independent, then "…clearly the random walk is not better than a coin toss at forecasting the exchange rate" (Engel, 1994). While Engel got better forecasting accuracy the longer time period he looked at, Meredith and Chinn (1998) have found that the rejection of the UIP hypothesis is more decisive the longer the time period between return dates.

The model we will use to describe the UIP deviations has its roots in Dueker and Neely (2007) where they use a Vector Error Correction Model (VECM) to forecast deviations from the UIP. The authors claim that since the UIP is a sort of risk premium, it should be governed by the risk aversion, and the safe-haven effects associated with a change in the variance of the underlying currency. They allow the model to differentiate between the variation of a variable, which affects the overall variance, and its frequency, which affects the kurtosis.

Chen, Roll and Ross (1986) investigated the linkages between stock returns and inflation, money growth, and a wide range of macroeconomic variables. They highlighted the importance of the term spread and industrial production growth in explaining stock return behavior. We believe that something similar could be valid for exchange rates as well, but that is beyond the scope of this study.

Our forecasting model is developed in a similar way as in Frömmel et al (2006), where the actual underlying model is of secondary importance as their main focus is on trying to explain the process for the switches between the regimes. The authors argue that fundamental variables do not only matter for the exchange rates, but also for the switches between regimes themselves. To explain this process the authors use a Logit model, where they include the fundamental variables. They find the variables to be significant factors to explain the switching process, suggesting that the regimes are not random indeed, and that they hence could be endogenized. However, there are two main drawbacks of their model. First, many of the variables in their paper are insignificant, and secondly, Faust et al (2003) argue that about one third of all improved forecasting over a random walk is eventually undone by data revisions. Hence, if fundamentals are to be included in the forecasting part in a study, it is almost always better to use real time fundamental data, than it is using ex post revised data.

In addition to fundamental data, a study by Gherig and Menkhoff (2006) reveals that 75% of all fund managers in their study use technical analysis (TA) in their short term currency trading, and for those who use it, it is also the main instrument for short term forecasting ranging from intraday to a few days. The use of technical analysis is exclusively related to the view that psychological influences matter in foreign exchange. However, regardless if technical analysis is the main tool for forecasting or not, Gherig and Menkhoff (2006) argue that it is still used together with other kinds of analysis to create a bigger picture. Thus we believe it would not be enough to include only one of the two kinds of data in our forecasts, and hence we use both fundamental indicators and TA in our analysis.

3. Data

Our data is compiled from Bloomberg and Datastream and spans from May 2000 to April 2010. We have the daily Open, High, Low and Closing prices for all trading days for the nine most traded currencies in the world (the G10 currencies) against the dollar. For our interest rates we have chosen to work with the interbank overnight interest rates. Additionally we have Bloomberg analyst estimates and actual outcomes for the gross domestic product (GDP), Non-Farm Payrolls (NFP), Consumer Confidence (CC) and ISM Manufacturing Index ranging from January 2001 to April 2010. The data is gathered with release dates, and not for the period they actually adhere. We divide the sample into two subsamples with our model estimation sample ranging from May 2000 to December 2007 and a test sample ranging from January 2008 to April 2010.

3.1 The Exchange and Interest rates

We use currency prices for nine of the most traded currency pairs against the US-dollar for the developed markets; Australia (AUD), Canada (CAD), Great Britain (GBP), Japan (JPY), New Zealand (NZD), Norway (NOK), Sweden (SEK), Switzerland (CHF), and the euro area (EUR). In cases where the price is quoted with the dollar in the numerator we have just inverted the price for that currency in order to provide a homogenous picture across all currencies with the US dollar consistently in the denominator.

Summary statistics are presented in Appendix 1. Notable is that the (positive) returns in the carry trade currencies NZD and the AUD have a strong negative skew, which is consistent with Brunnermeier et. al. (2009) and Christoffersen and Diebold (2004). A correlation matrix can be found in Appendix 2. The most correlated currencies are the CHF vs. the EUR with a 0.90 correlation with the SEK vs. EUR as close second with a correlation of 0.84. Also noteworthy is that all the currencies, except for the GBP, have appreciated against the dollar.

3.2 The UIP

We have constructed the UIP by taking the difference of the log of two consecutive closing rates per different currencies, and then subtracting the overnight annualized interest rates. This yields the UIP defined as equation (1).

$$r_t = \ln(S_t) - \ln(S_{t-1}) + \ln(1 + i_t^*) - \ln(1 + i_t) \tag{1}$$

where i^* and i are the foreign and domestic interest rates respectively.

In Appendix 4, we show the summary statistics for the UIP. Notable is that the mean per day for all currencies varies between -1 and +3 basis points (bps) and the JPY is the only currency in the sample with a cumulative negative value.

The NZD has the most volatile UIP in the sample with a standard deviation of .0076, while the CAD has the lowest variance in the sample with a standard deviation of .0048. The Jarque Berra test for normality can be rejected on all levels, suggesting that the data is not normally distributed.

3.3 The Fundamental Variables

According to the Efficient Market Hypothesis (EMH) all the information available to investors should already be incorporated in the market prices (Fama 1970), but since the information is continuous and expectations can change quickly, it can be quite difficult to estimate the isolated impact of different variables on the exchange rate. We have tried to overcome this problem by looking at what happens when the market expectations are wrong. By regressing the estimated state on the difference between the Bloomberg estimated values of data releases and their actual outcomes, we are hoping to get a more accurate picture of how the variables themselves affect the markets, without the influence of market excess sentiment. The Bloomberg estimates are based on an average of reported estimates from different financial institutions that have chosen to include their estimates in the survey. We thus assume that these expectations, surveyed by Bloomberg, accurately reflect the prevailing market sentiment at that point in time. By combining these two measures we would get a shock indicator and something in the fundamental macroeconomic variables the markets have failed to price in. Summary statistics and graphs for our fundamental variables are included in Appendix 4.

We will be using different macroeconomic data together with TA indicators to assess the change in demand for the currency. Since we have chosen to look at all the currencies compared to the U.S. dollar, we will include data from the U.S in all our regressions. The measures we have chosen have been decided on based on Fair (2003) and through further discussion with Olsson (2010). Fair (2003) looks at the market impact for various variables when they are released and specify that they have a significant impact if the price increases within the next minutes.

Our first macro variable, the Gross Domestic Product (GDP), is arguably the most well known macroeconomic variable among all our chosen variables. GDP is released by the Bureau of Economic Analysis the first Friday after a quarter ending. The average of the deviation between the estimates and the actual outcome is slightly negative (-0.04), meaning that the actual numbers on average have been slightly worse than expectations.

The second variable, Non-farm payrolls (NFP) is a statistic researched, recorded and then reported the first Friday every month by the U.S. Bureau of Labor Statistics and functions as an approximation for the unemployment in the U.S. The average deviation for this measure is slightly negative as well, suggesting that the markets on average have been slightly more optimistic than the outcome.

The Consumer Confidence Index (CC), our third variable, is an index released once a month by the Conference Board, and measures how optimistic the American consumer is about both the current and future economic situation. This index, as opposed to the Michigan index, only has minor revisions which is beneficial as well. The index has a slightly negative bias of -0.23, but the standard deviation is 5.3 which is the highest in the sample.

Our last macro variable we have decided to include is the ISM Manufacturing Index (ISM). Released on the first business day of the month by The Institute of Supply Management, this index tries to mirror how well the US manufacturing sector is doing at the moment. On average this index surprises the market positively in our sample, with a mean of 0.25.

3.4 Technical Indicators

The technical indicators we will use are the Relative Strength Index (RSI), the Moving Average Convergence/Divergence (MACD) and the stochastic measure %D. Technical variables work by using past prices to make inferences about future prices. According to the EMH, this should not be possible. However, as the review of the literature has revealed, people tend to look at these variables regardless, possible suggesting that the markets are not as efficient as some people believe but be that as it may, we will still investigate if these variables can have an impact on the deviations from the UIP. Since all the indicators produce sell or buy signals, we have chosen to divide them into two binary variables each for buy and sell signals respectively. Another computational issue is that some traders use exponential moving averages and others use equally weighted moving averages for the variables, but we have chosen to include the equally weighted moving average for computational simplifications. Summary statistics and graphs for our technical variables are included in Appendix 6.

Our first variable, the RSI, was developed by J. Welles Wilder and is one of the more popular indicators among traders (Murphy 1999) The RSI works by comparing the size of the gains to the losses over a specified period of time and is computed in two steps using equation (2) and (3).

$$RS = \frac{Average\ of\ x\ days'\ up\ closes}{Average\ of\ x\ days'\ down\ closes} \qquad (2)$$

$$RSI = 100 - \frac{100}{1 + RS} \qquad (3)$$

In our model we have used x=14 days since Murphy (1999) claims it is the norm. The premise is that if the index reaches a value above 70, then the asset is overbought and should therefore head south or slow down in positive momentum. On the other hand, if the index reaches a value below 30, the asset is oversold and should head north or slow down in negative momentum. The term relative strength is not to be confused with when comparing the relative attractiveness for different entities such as stocks versus bonds, but this measure is rather focusing on in which direction the price of something is heading. The drawback, according to Murphy (1999) is that in strong trends in any direction, the RSI index can stay overbought or oversold for extended periods of time, which understandably could produce false signals.

Our second indicator is the MACD, which is a momentum indicator that combines three moving averages. The difference between a 12-period and a 26-period moving average (this difference is known as the MACD line) is compared to a 9-period moving average (known as the Signal line). When the signal line is below (above) the MACD and then crosses after a couple of periods, a buy (sell) signal is created, signaling that the momentum is about to change.

For our variables we have chosen to include the crossing of the line as the signal, making the deciding factor for the binary variable to be decided by equation (4) and (5).

$$x_t = \left(MACD_{12,26,t} - Signal_{9,t}\right)$$

$$x_{t-1} = \left(MACD_{12,26,t-1} - Signal_{9,t-1}\right)$$

$$MACD_{buy} = f(x_t, x_{t-1}) = 1 \quad if\ x_{t-1} < 0\ and\ \ x_t > 0 \qquad (4)$$

$$= 0 \quad else$$

$$MACD_{s\,ell} = f(x_t, x_{t-1}) = 1 \quad if\ x_{t-1} > 0\ and\ \ x_t < 0 \qquad (5)$$

$$= 0 \quad else$$

The third technical variable we use is the %D indicator which utilizes intra-day data to give a measure on how close to the extremes of the daily range the currency closes. The premise is that the asset usually closes in closer proximity to the highs of the day if the trend is strongly positive, and towards the lows of the day is the trend is negative. If a currency would have a positive ten day history, and closes in positive territory but closer to the lows of the period, that might be an indicator that the trend is about to reverse. (Murphy 1999)

The measures is calculated as in equation (6) and (7).

$$\%K = 100 * \frac{(Close - Lowest\ x\ days'\ lows)}{(Highest\ x\ days'\ highs - Lowest\ x\ days'\ lows)} \qquad (6)$$

$$\%D = 3 - period\ Moving\ average\ of\ \%K \qquad (7)$$

Where, as in the case of the RSI, we have used x=14. The buy (sell) signal comes when the %K line is below (above) the %D line and crosses it at the same time as the %K line is below 20 (above 80). As opposed to the fundamental data, the technical indicators are allowed to fluctuate more frequently due to their daily updates. Depending on the volatility of the currency, signals might come more or less frequently.

4. Methodology

4.1 The Uncovered Interest Parity

We start from the UIP and the efficient market hypothesis stating that expectations of currency fluctuations will depend on the interest rate differential between two countries. We implement a similar model to the one used in Dueker and Neely (2007) to explain deviations from the UIP by, as earlier, denoting the deviation from the UIP as equation (1), recall that

$$r_t = \ln(S_t) - \ln(S_{t-1}) + \ln(1 + i_t^*) - \ln(1 + i_t) \quad (1)$$

The interest rate differentials have been calculated as in equation (8).

$$\ln(1 + i_t^*) - \ln(1 + i_t) = ln\left(1 + \left(\frac{r_t^* * (n_t - n_{t-1})}{360}\right)\right) - ln\left(1 + \left(\frac{r_t * (n_t - n_{t-1})}{360}\right)\right) \quad (8)$$

Where r and r* is the yearly nominated domestic and foreign interest rates respectively. In this equation the interest rate differential has been adjusted for weekends and non-trading holidays, so that $(n_t - n_{t-1})$ is equal to the amount of days between two observations.

The deviation of the UIP can be described as a discrete time process with a time varying drift and variance such as;

$r_t = \mu_t + \sigma_t * \epsilon$

Where $\epsilon \sim N(0,1)$

Since the MS process (explained below) is set up with four states with own distributions for every state, we find the normality assumption to be fair. Even though The Jarque Berra test has a p-value of zero (see Appendix 5) which suggests a non-normal distribution, we still believe we can assume the r_t to be normally distributed due to the time varying characteristics of mean and variance. The Dickey Fuller tests for stationarity were also rejected, suggesting that our data is at least weakly dependent (see Appendix 3).

4.2 The Markov Switching Model

In the model we use two independent Markov chains, s_t and z_t, that each can take the value 0 or 1. The underlying Markov chains are then used to model the time-varying μ_t and σ_t as in equation (9) and (10).

$$\mu_t = \lambda_0^{\mu} + \lambda_1^{\mu} * z_t + \lambda_2^{\mu} * s_t \qquad (9)$$

$$\sigma_t^2 = \lambda_0^{\sigma} + \lambda_1^{\sigma} * z_t \qquad (10)$$

This approach is similar to the one developed in Dueker and Neely (2006), without allowing for higher moments such as kurtosis to affect the returns. The specification allows the outcome to be in $2^2 = 4$ different regimes and adds a non-linear relationship between μ and σ^2. Based on the Merton model (Merton 1974) this is a plausible specification since it assumes that there is some relationship between μ and σ^2, but it doesn't have to be linear. The model will estimate four different combinations of μ and σ^2 for the deviations from the UIP for each country. However, since we cannot observe the Markov chains, but only their conditional probabilities, the expected deviations from the UIP is dependent on the probabilities of the Markov chains. Hence, the UIP in our model can take a continuous set of values within the boundaries set by our estimated parameters.

The conditional probabilities of entering a regime in the next time period, given the prevailing regime, can be found in the transition probability matrix P. Given the independence of each Markov chain we can construct the 4X4 transition probability matrix by combining the 2X2 matrices for z and s as:

$$\begin{bmatrix} p_{11}^z & 1-p_{22}^z \\ 1-p_{11}^z & p_{22}^z \end{bmatrix} \otimes \begin{bmatrix} p_{11}^s & 1-p_{22}^s \\ 1-p_{11}^s & p_{22}^s \end{bmatrix} =$$

$$= \begin{bmatrix} p_{11}^z * \begin{bmatrix} p_{11}^s & 1-p_{22}^s \\ 1-p_{11}^s & p_{22}^s \end{bmatrix} & (1-p_{22}^z) * \begin{bmatrix} p_{11}^s & 1-p_{22}^s \\ 1-p_{11}^s & p_{22}^s \end{bmatrix} \\ (1-p_{11}^z) * \begin{bmatrix} p_{11}^s & 1-p_{22}^s \\ 1-p_{11}^s & p_{22}^s \end{bmatrix} & p_{22}^z * \begin{bmatrix} p_{11}^s & 1-p_{22}^s \\ 1-p_{11}^s & p_{22}^s \end{bmatrix} \end{bmatrix}$$

where $p_{ij}^{a} = p(a_t = i | a_{t-1} = j)$ for $a = \{z, s\}$ and $i, j = \{0,1\}$

The higher is p_{ii}^a the longer chain a is expected to remain in state i. For this reason we shall refer to p_{ii}^a as measuring the persistence of the underlying regime. We assume to find different persistence measures depending on the nature of the regime. Regimes with near zero deviations from the UIP combined with high volatility will presumably be more persistent and high absolute abnormal deviations combined with low volatility will be less persistent.

The model is implemented in MATLAB using a code package initially developed by Perlin (2009), but rewritten to allow for two independent Markov chains, instead of one as initially was intended.

The normality assumption gives the conditional density function of r_t as in equation (11).

$$f(r_t|\theta) = \sum_{j=0}^{1}\sum_{i=0}^{1} \frac{\pi_i^z * \pi_j^s}{\sqrt{2*\pi} * \sigma_i} \exp\left(-\frac{r_t - \mu_{ij}}{2\sigma_i}\right) \qquad (11)$$

Where π_i^s and π_j^z are the conditional probability of s and z being in regime i and j, respectively. The notion of θ is the parameter vector containing all estimated parameters $\{\lambda_0^\mu, \lambda_1^\mu, \lambda_2^\mu, \lambda_0^\sigma, \lambda_1^\sigma, \pi_{11}^z, \pi_{22}^z, \pi_{11}^s, \pi_{22}^s\}$.

Hamilton (1994) shows that the numerical solution to the MS parameters is the one that maximizes the log-likelihood function as stated in equation (12).

$$\mathcal{L}(\theta) = \sum_{t=1}^{T} \ln\big(f(r_t|\theta)\big) \qquad (12)$$

The maximization procedure will produce best-fit estimates for our chain parameters of μ and σ and will also give the respective 2x2 probability matrix for each chain. This is done by setting starting values for the different parameters and using an optimization algorithm to reach the maximum likelihood. From the transition matrices, we can back out the smoothed unconditional probabilities of each chain being 0 or 1 at any given point in time. Additionally, the density function $f(r_t|\theta)$will supply the filtered conditional probabilities for each chain being 0 or 1 at any given point in time.

Standard errors for the estimated parameters will be calculated using the outer product matrix (OP matrix) as an approximation for the Information matrix.

4.3 The Logit Model

In theory and also in Dueker and Neely (2007) and Guidolin et. al. (2009) the Markov chains are assumed to be unobservable and random, so while we can allow for the presence of regimes, we should not be able to exogenously impose or characterize them with certainty. However, once our model has managed to describe the deviations from the UIP, we will try to endogenize s_t and z_t by using our fundamental and technical indicators as exogenous variables.

Furthermore, we know that the expected value for each chain have to be within the interval {0:1}, not allowing for negative probabilities and probabilities above 1. Consequently, this data does not have optimal statistical properties for a regular OLS linear model, as it has very clear boundaries. We solve this problem in two steps. First, we filter the probabilities using a threshold stating that if the probability exceeds the threshold, the chain will be assumed to be in state 1, otherwise in state 0. This will produce a binary variable for each chain being in state 0 or 1 across the whole time sample. Second, we apply a Logit model, where we define a new variable y_t (equation (13)) that transforms the binary variable into an unconstrained variable that can take on any real number.

$$y_t^a = \log\left(\frac{p(\mathrm{a}_t = 1)}{1 - p(\mathrm{a}_t = 1)}\right) \; for \; a = \{z, s\} \qquad (13)$$

These will then be the endogenous variables in our Logit regressions where we investigate whether the expected value of each chain can be forecasted using our technical and fundamental indicators.

The threshold that we use to filter the probabilities through into binary variables is highly discretional. Frömmel et. al. use a threshold of 0.5 to define their variable, which means that if the probability of being in that state is above 0.5 they define that observations as being in state 1. Engel (1994) compare this threshold to the probability of making type one and type two errors. Thus, a crucial difficulty is to know where to set the threshold to identify when the chain actually is in a certain state. From the transition matrices for z and s we can calculate the long term unconditional probability of being in state 1 as equation (14).

$$\mathrm{p(z = 1)} = \frac{1 - p_{11}}{2 - p_{11} - p_{22}} \qquad (14)$$

After having calculated the long term unconditional probabilities from the MS model, we use an algorithm to find the threshold that filters the data in such a way that the expected value of the binary variable corresponds reasonably well to this long term probability.

This unconstrained variable can then be estimated in a Logit regression using a log-likelihood approach to capture the effect of the fundamental and technical indicators. We specify three different Logit models to see if fundamental or technical indicators alone give a better or worse outcome than a combined model.

From the Markov estimation we will get a smoothed probability for each chain at each given point in time as equation (15) and (16).

$$p(s_t = i|y_{t-1}, \theta_{t-1}) = \pi_t^s \; for \; i = \{0,1\} \qquad (15)$$
$$p(z_t = i|y_{t-1}, \theta_{t-1}) = \pi_t^z \; for \; i = \{0,1\} \qquad (16)$$

To discover if our technical and fundamental indicators have some forecasting ability regarding the regime shifts we run a Logit regression as

$$y_t^a = \beta_{0,\mathrm{a}} + \beta_{1,\mathrm{a}} * GDP_{t-1} + \beta_{2,\mathrm{a}} * NFP_{t-1} + \beta_{3,\mathrm{a}} * ISM_{t-1} + \beta_{4,\mathrm{a}} * CC_{t-1} + \beta_{5,\mathrm{a}} * RSI_{t-1}^{Buy}$$
$$+\beta_{6,\mathrm{a}} * RSI_{t-1}^{Sell} + \beta_{7,\mathrm{a}} * MACD_{t-1}^{Buy} + \beta_{8,\mathrm{a}} * MACD_{t-1}^{Sell} + \beta_{9,\mathrm{a}} * \%D_{t-1}^{\mathrm{Buy}} + \beta_{10,\mathrm{a}} * \%D_{t-1}^{\mathrm{Sell}} + \varepsilon_t$$

$for \; a = \{z, s\}$

We assume that ε_t is homoskedastic and normally distributed and examine the model fit and possible model miss specification by running constrained versions of the above model using only technical and fundamental indicators respectively. We also check for robustness by investigating if there is any difference in using filtered or smoothed probabilities as a base for the dependent variable.

Finally the fit of the different models will be assessed by a chi-square measure, comparing the log likelihood of the different models. A model with more variables will always have as low or lower log-likelihood as a model with fewer variables. Hence we need to compare the models to see which specification is the best one.

4.4 Simulation

Based on the model we have estimated through our MS and Logit models we will be able to make statistical inferences about the model's ability to describe our sample data. To further discover the validity of our model we set up a simulation on out of sample data. As described by Dueker and Neely (2007), the empirical results can be complemented with the results from a trading rule based on these simulations to see if the model has an economic importance as well.

The simulation will be done in two steps. First we look at the outcome of our technical and fundamental indicators and put them into our Logit model to forecast which regime we are likely to encounter tomorrow.

$$\hat{y}_t^a = \hat{\beta}_{0,a} + \hat{\beta}_{1,a} * GDP_{t-1} + \hat{\beta}_{2,a} * NFP_{t-1} + \hat{\beta}_{3,a} * ISM_{t-1} + \hat{\beta}_{4,a} * CC_{t-1} + \hat{\beta}_{5,a} * RSI_{t-1}^{Buy} + \hat{\beta}_{6,a} * RSI_{t-1}^{Sell} + \hat{\beta}_{7,a} * MACD_{t-1}^{Buy} + \hat{\beta}_{8,a} * MACD_{t-1}^{Sell} + \hat{\beta}_{9,a} * \%D_{t-1}^{\mathrm{Buy}} + \hat{\beta}_{10,a} * \%D_{t-1}^{\mathrm{Sell}} + \widehat{u_t^a}$$

$$for\ a = \{z, s\} \quad where\ the\ residual\ \widehat{u_t^a} \sim N(0, \sigma_{u_a}^2)$$

To calculate the expected value of z and s at any given time, we use the above specification but only include the indicators for which we find significant betas in our in-sample estimation. The estimated results of $\hat{y}_t^s$ and $\hat{y}_t^z$ are translated back to probabilities of s_t and z_t according to equation (17).

$$p(a = 1) = E(a_t) = \frac{e^{\frac{\sigma_{u_a}^2}{2}} * e^{\hat{y}_t^a}}{1 + e^{\frac{\sigma_{u_a}^2}{2}} * e^{\hat{y}_t^a}} \quad for\ a = \{z, s\} \qquad (17)$$

Notice that this is not a direct reversion of the Logit model. We apply this to avoid the bias that occurs according to (Wooldridge 2009). Second, the conditional probabilities from our Logit simulation will serve as base to calculate the time-varying conditional mean and variance of r_t. This will be done by using the significant variables from the MS model in the below formulas.

$$E\big(\mu_t \big| E(z_t, s_t)\big) = \hat{\lambda}_0^\mu + \hat{\lambda}_1^\mu * E(z_t) + \hat{\lambda}_2^\mu * E(s_t)$$

$$E\left(\sigma_t^2 \middle| E(z_t)\right) = \hat{\lambda}_0^\sigma + \hat{\lambda}_1^\sigma * E(z_t)$$

4.5 Trading rule from the MS model

The trading rule will be implemented by inserting our forecasts as expected values of each Markov chain, $E(z_t)$ and $E(s_t)$, into the base specified model for $\hat{\mu}_{t+1}$ and $\hat{\sigma}_{t+1}$ to get the expected deviation and variance for the next specified time period. Since trading is much about risk reward (Sharpe 1966) we differ slightly from other papers in the literature, since to our knowledge, they only control for increased risk only after the trades have been made. We argue that in order to make sure we get a decent risk reward it is preferred to consider a measure which is similar to the Sharpe ratio, a risk reward measure (RR), prior to investing. The reason for why we are differing from the Sharpe ratio is that the UIP is already adjusted for interest rates, and thus we need not to adjust it again at this point for the sake of our purposes.

The estimated RR (ψ) will be calculated as equation (18)

$$\psi_t^i = \frac{E\left(\mu_t \middle| E(z_t, s_t)\right)}{E\left(\sigma_t \middle| E(z_t)\right)} \qquad (18)$$

To invest in a currency we specify thresholds where we go long if the expected RR is higher than the filter level, exit the market if the RR is in between the filter levels, and go short if the RR is below the filter level. Since different currencies are perceived to have different risks we thus need currency specific RR ratios to set the individual filter levels. To decide what RR filter rules to use we look at the mean of the historically simulated RR ratios (in sample simulation) and chose the filter levels as standard deviations from the mean. This means that we do not have to adjust the levels automatically for every currency since the trading rule will be implemented automatically. The reason for using standard deviations from the mean depends on the risk tolerance of people. If we use a very strict trading rule, like two standard deviations from the mean, it means that we only would act on predicted signals that are with 95% certainty higher than the true population mean. This translates to the need for a high risk reward and should result in few and short trades with lower profits, compared to a trading rule with a cutoff of one standard deviation from the mean, which would lead to not only more trades but also longer duration of each trade.

First we define the positions as;

$\omega = 1 \rightarrow Long\ position\ in\ the\ UIP$

$\omega = 0 \rightarrow No\ position\ in\ the\ UIP$

$\omega = -1 \rightarrow Short\ position\ in\ the\ UIP$

The general rule is then:

$if\ \psi_t^i > \bar{\psi}^i + \tau\sigma_\psi^i \rightarrow \omega_t = 1$

$if\ \psi_t^i < \bar{\psi}^i - \tau\sigma_\psi^i \rightarrow \omega_t = -1$

$Else\ \omega_t = 0$

Where the ψ_t^i is the estimated RR ratio, $\bar{\psi}^i$ is the historically simulated mean of the RR ratio, τ is the strictness variable which we use to assess the risk aversion, and σ_ψ^i is the historically simulated standard deviation.

These positions are re-evaluated at every time period to see if we should keep our position or make a trade to either enter or exit the markets. Compared to a regular trend following model, this model can decide if a trade is worth entering the market for or not, depending on the risk reward.

In addition, if we are able to evaluate several currencies at the same time, so that we are provided with more investment opportunities, our model can trade those currencies simultaneously.

By not only assuming that we can go long or short, but also assuming that we can remain outside the market for an extended period of time without pressure from investors, this strategy reduces our transaction costs and minimizes our exposure to unwanted market volatility.

4.6 Excess return Calculation

The excess returns will be calculated using an aggregate measure over the year which is dependent on how the positions have been doing over the year.

$$return_i = \sum_{i=0}^{\mathrm{T}} \omega_t * UIP_t - \mathrm{nc}$$

Where n is the number of trades, and c is the cost per trade

Since we only look at the period ahead and not a cumulative average, as many other papers in the literature do. In this setting we know when to enter or exit the market but without a previously expected cumulative excess return. Ex-post we will find out how good our investment was, but we do not calculate the ex-ante expected returns. Hence, if we include trading costs in our trading rule, we could often experience an expected loss for the first day, if the expected profit is not larger than the one day excess return. Hence we include the transaction costs after our trades have been made and use a cost of relatively large 10bps per trade.

4.7 Statistical Performance Measures

Comparisons of forecast accuracy are thus of importance to forecasters choosing among different models. Predictive performance and model specification are fundamentally linked as predictive failure implies model misspecifications (Diebold and Mariano 1995). To see how well our model adapts to the out of sample data we will mainly look at three statistics.

Firstly, the percentage correct sign predictions at the one day forecast horizon is the main predictor as we both have comparisons in from the in-sample data and the comparisons with other papers such as Dueker and Neely (2007) and Dewachter (2001).

Our other two measures are the Mean Square Error (MSE) and the Mean Absolute Error (MAE) will be compared to a naive constant return model, and should hence be comparable to the previously mentioned papers as well. Naturally, since all the models are based on different time samples they will produce slightly different output and will not directly be comparable to our estimates for the sake of model comparison. However, we believe that this could yield an adequate understanding of the fit of our model as a whole.

5. Estimation Results

5.1 Results from MS

In order to reach solutions for each currency we need to specify starting values which give the best possible fit for the in-sample returns. We perform a grid search approach to find the best starting values for our parameters in order to reach a plausible solution to the log likelihood maximization problem. For some currencies the model is very sensitive to alteration of the starting values, hence making the estimation process fairly complex. The reason for this is the unknown distribution of the log likelihood function that implies that we cannot know if the final solution is reached at a global or local maximum. We manage to describe the process for all currencies except for the SEK, for which we cannot find any starting values so that our model is able to reach a solution.

Our results from the MS model have been included in Appendix 7. In all our regressions we can identify two extremes, with one good state and one bad state, with two intermediate states in between, so that;

$$State\ 1 = \mu_1 = \lambda_0^{\mu} + \lambda_1^{\mu} + \lambda_2^{\mu}$$
$$State\ 2 = \mu_2 = \lambda_0^{\mu} + \lambda_1^{\mu}$$
$$State\ 3 = \mu_3 = \lambda_0^{\mu} + \lambda_2^{\mu}$$
$$State\ 4 = \mu_4 = \lambda_0$$

With the variances given by;

$$\sigma_{low}^2 = \lambda_0^{\sigma}$$
$$\sigma_{high}^2 = \lambda_0^{\sigma} + \lambda_1^{\sigma}$$

The low variance applies to state 3 and 4 and the high variance to state 1 and 2.

We classify the state with high absolute expected return and low variance as the good state (state 3), and the state with low absolute return, and high variance as the bad state (state 2). Our significant coefficients with signs are presented in Table 1.

TABLE 1. Deviation - Sign and significance

	EUR	*JPY*	*GBP*	*CHF*	*CAD*	*AUD*	*NZD*	*NOK*
$\boldsymbol{\lambda_0^{\mu}}$	0	-	+	0	0	+	+	+
$\boldsymbol{\lambda_1^{\mu}}$	0	+	0	-	+	0	-	0
$\boldsymbol{\lambda_2^{\mu}}$	-	-	-	+	0	-	-	-
State 1	-	-	-	+	0	-	-	-
State 2	0	0	0	-	0	0	0	0
State 3	-	-	-	+	0	-	-	-
State 4	0	-	+	0	0	+	+	+

From Table 1 we can see that the GBP, AUD and the NOK have the same parameter setup, i.e. they have the same sign for all the significant coefficients. However, the dominant states differ as the AUD has its dominant state in state 4, where the UIP is slightly positive and volatility is lower, while the NOK and the GBP find persistence in state 2, in which the UIP deviation is not significantly different from zero and volatility is higher. Another similarity is that all three currencies have strong persistence in s being zero, meaning a more positive deviation from the UIP.

The difference between these currencies is the duration in the chains governing the regimes. The AUD has a slightly shorter duration of the regimes, ranging from 135 days for z, while the NOK has duration of over 250 days for z and the GBP is above 500.

The CHF has a very good explanatory power, as all the variables, except for the intercept and hence state 4, are significantly different from zero on a 5% level. The regimes are predicted to have a duration of 0.14-3 days for the significant states. The most dominant state is state 4, which has a non-significant deviation from the UIP.

The EUR and the JPY has one common denominator, which is that the deviation from the UIP is either negative or insignificant at a 5% level for all states. This implies that the model will never predict a positive return.

In total, our results show that state 2, which is the state with high variance and low mean, is the most persistent state across all currencies, except for the AUD and NZD which have state 4 as the dominant state. Moreover, we find the variance parameters to be highly significant in all currencies in the sample, suggesting that we consequently have higher variance for state 1 and 2 than state 3 and 4.

We see that the deviation for state 2, which is the state with low absolute return and high variance, is not significantly different from zero in seven out of eight currencies. However, state 1 and 3 with high absolute returns compared to the variance are significantly different from zero for all currencies, except for the CAD, indicating that it is possible to reach a state in which the return is not expected to be zero.

5.2 Results from the Logit estimation

Appendix 8 shows how good fit of the Logit model for both chain z and chain s we get if we use either fundamental, technical or both fundamental and technical indicators. The combined model includes both fundamental and technical indicators. To specify which model that is preferred we need to compare all specifications against each other by using two specification tests. A likelihood-ratio test is used for the nested models and calculates the p-value for the null hypothesis that they do not differ in explanatory value against the alternative that they do. The Davidson-MacKinnon test for the non-nested models tests the null hypothesis that using fundamental variables or technical indicators are equally good against the alternative that using technical indicators are better (see Appendix 8).

For chain z the results are inconclusive, meaning that for some currencies the combined model specification is the better, while others imply that either the fundamental or technical specification is the better. The EUR and the CHF results explain that we cannot say that the combined model has any higher explanatory power than just using technical indicators. However, the combined model is better than using fundamental variables only. For the JPY, GBP, CAD, AUD and NZD we can conclude that using the combined model adds value against using any of the other models, while the fundamentals always have a higher explanatory value against technical indicators. For the NOK we find that using the combined model adds value to the technical indicators only specification, but the combined model cannot be said to be better than the fundamentals only model. The last two currencies, EUR and CHF, indicate that either the combined model or the technical indicators provides the best model specification.

For chain s we see that EUR, JPY, GBP, CAD and AUD are either inconclusive or prefer the combined model specification, while the other three currencies do not reject the technical model specification.

Appendix 9 presents the estimated variables and significance level from our Logit regressions. The output from the Logit regressions affirms what could be seen in the fit of the Logit regression, which is that for some currencies technical variables seem to be more or less important. For z we have that in the case of the NOK, technical variables do not seem to matter at all, and for the EUR, JPY and the CHF, none of the fundamental variables are significant. For the GBP both fundamental and technical indicators seem to have an effect. The RSI variables are highly significant for both the AUD and the NZD, while the MACD variables are significant for the JPY, but with the same sign on the coefficients. Among all variables, the GDP and ISM are the ones that are significant for the most currencies.

For chain s we see that only three of the currencies, not counting the CAD, are affected by our variables on a 5% significance level and evidence is mixed whether it is fundamental or technical indicators driving the regime shifts. For the JPY and the CHF, GDP is negative and significant, while the NFP is negative but significant only for the CHF. MACD buy is also significant and positive, while the RSI sell is significant and negative for the CHF and positive for the NZD respectively.

The CAD is a special case since it did not have any significant returns in the MS model. However, the variance is still affected by z, and thus we can make some inferences about the variance but not the mean. The variance for the CAD seems to be driven almost exclusively by fundamentals and not technical variables. All the variables are significant, even though the variable for ISM is close to zero and thus lack economic significance. The one technical variable that influences the variance is RSI sell, which has a negative coefficient.

5.3 Results from trading rule

The results from the out of sample simulation yield promising results. A full summary of our trading results can be found in Appendix 10.

For the most lax trading rule, using only the fundamental variables our profit was on average 2.95% per annum (p.a.), ranging from a loss of -6.71% p.a. for the JPY to a 19.49% p.a. gain for the NOK. Since the CAD has four insignificant states, it did not trade at all and hence we don not include it when calculating the averages for the payoff. For the slightly safer trading rule, with +/-1.5 standard deviations from the historical mean set as the filter, we find that our model has an average of 3.11% p.a., with the only negative value of -1.2% for the JPY, while yielding 11% for the NOK and 9.4% for the AUD. With the even stricter trading rule of +/-2 standard deviations from the mean, the average drops substantially and the strictest trading rule has an average return of 0.90% p.a.

Only using technical variables in the process makes our returns decrease significantly compared to only using fundamental variables. With an average loss of -0.85% for the loosest rule, the trading produces significant losses compared to the fundamentals only model. One difference seems to lie in the trading costs which almost double with the technical model, i.e. we make more trades. However, even when not considering the trading costs at all, the technical model fails to beat the fundamentals only model, since the average return is just above zero. Additionally, the returns between the strictness of the trading rules are turning less negative the stricter the rule, with the strictest rule having a slightly positive yield of 0.37%.

The total profit from using both the technical indicators and the fundamental variables gives the highest yield for the two most lax rules, and the lowest yield for the two strictest rules. Yielding 2.37% the combined model gives a slight decrease in profits compared to the fundamentals only model, but the before costs profit differs less since adding technical indicators to the analysis increases the amount of signals, which causes the trading costs to be higher.

5.4 Statistical Criteria

Table 2 summarizes our statistical findings for our forecasts. For the in sample data we can see that our model performs as well as or better than the naive constant return model. The %Right statistic implies that our model beats a coin toss for every currency, suggesting that it provides a good fit on in sample data.

Looking at the out of sample data we can see that the combined Logit model specification does provide a better forecast than the naïve constant return model for all currencies except JPY. However, there are some mixed evidence for the AUD and NZD since the MAE and MSE are above unity at one occasion each. For the %Right statistic we can see again that we get the correct sign more than half of the time for all currencies except the JPY.

Taking into account the technical indicators only, we see that again our model manage to beat the naïve constant return model for all currencies except JPY and NZD. As with the combined model we find mixed evidence for the AUD. The %Right statistic gives similar results as for the combined model.

TABLE 2. MS Model Fit

	EUR	*JPY*	*GBP*	*CHF*	*CAD*	*AUD*	*NZD*	*NOK*
In Sample								
MAE	0,9997	0,9995	0,9989	0,9978	0,9989	1,0016	1,0015	0,9989
MSE	0,9996	1,0004	0,9983	0,9959	0,9984	0,9999	0,9992	0,9989
%Right	0,5180	0,5286	0,5221	0,5095	0,5241	0,5362	0,5327	0,5240
Out of Sample (Fund & Tech)								
MAE	0,9976	1,0083	0,9975	0,9972	0,9996	1,0005	0,9995	0,9981
MSE	0,9986	1,0151	0,9967	0,9985	0,9994	0,9997	1,0003	0,9977
%Right	0,5124	0,4959	0,5357	0,5058	0,0000	0,5290	0,5091	0,5556
Out of Sample (Tech)								
MAE	0,9976	1,0072	0,9977	0,9972	0,9996	1,0003	1,0001	0,9993
MSE	0,9987	1,0128	0,9974	0,9984	0,9994	0,9996	1,0013	0,9996
%Right	0,5124	0,4959	0,5489	0,5058	0,0000	0,5439	0,5008	0,5025
Out of Sample (Fund)								
MAE	0,9977	1,0070	0,9979	0,9993	0,9996	0,9999	0,9995	0,9981
MSE	0,9984	1,0130	0,9967	1,0001	0,9994	0,9987	0,9996	0,9977
%Right	0,5124	0,4959	0,5456	0,5091	0,0000	0,5390	0,5191	0,5473

In the fundamental variables only specification we see that our model outperforms the naïve model to an even greater extent than the combined model. The JPY is again the only currency where we fail to do better forecasts then the naïve model. From the %Right statistic we see that the JPY is also the only currency for which we on average fail to predict the right sign.

Overall it is noticeable that for our out of sample simulations we manage to even more efficiently predict the right sign on the GBP, AUD and NZD compared to our in sample forecasts.

6. Analysis

The MS Model

Our model generally has two extreme states. One with high absolute return together with low variance and one with low absolute return together with high variance. On top of this each currency has two intermediary states it passes to go from one extreme to the other. Menzly et al (2002) compares this with having periods of varying forecastability, since it would be harder to estimate the low mean/high variance, and easier to estimate the states where the roles are reversed. Our results show that state 2, previously referred to as the UIP state, with low mean high variance, is the most common one. Thus, since we are in the UIP state most of the time, this suggests a firm support for the UIP hypothesis, but only for small time periods. This is an interesting finding since many other papers have rejected it. However, since we are applying an MS-model we can still predict the deviations from the UIP when opportunity arises.

Looking at the AUD and NZD, investors speculating in carry trades thus experience times with both state 4, and the UIP state. Hence, the forward premium puzzle, which is prevalent in state 4, could still exist without the need for rejecting the UIP.

Looking at the other currencies we can see that most of the currencies are hesitant between state 2 and state 4, which means that the most common currencies are divided in between the UIP and the intercept in the MS-estimation (λ_0^{μ}). The CAD is special in the sense that none of the states have a significant return. This would suggest that the CAD is a pure UIP currency in our model, and hence we should not be able to forecast it very well in terms of mean return. However, since we found the parameters for the variance to be significant, a very useful application of this might be in forecasting of the implied volatility or currency options. Since prices are often measured in implied volatility, our model might be able to predict some of the "return" in option trading. Since this is beyond the scope of this paper we will not develop this thought further, but add that it could be an interesting field for future research.

Furthermore it is interesting to see that for three currencies, GBP, AUD and NOK, we actually get an even better prediction on the sign of the return using out of sample data rather than in sample data. Comparing the statistical criteria to results from previous research, our results have outstanding performance. This would suggest that our model on average outperforms a random walk. However, due to various uncertainties, among them the previously discussed peso problem, we find it hard to draw any conclusions from this finding. For example, the EUR, JPY and CAD have only negative or insignificant return over the four states, suggesting our model will never predict a positive return. We cannot with certainty conclude that there are no states in which the return is positive, but given our model and the data that we have used we can say that positive returns are much less prevalent than negative returns. A possible explanation for the JPY is the safe haven effects mentioned earlier, in which investors prefer safer currencies when markets become uneasy. In this setting, investors would view the JPY to be somewhat safer than the USD during some periods of time, which is plausible in light of the recent years' financial crisis.

Another finding is that for some currencies the MAE and MSE statistical criteria yield inconclusive results. Dueker and Neely (2007) argue that this could steam from extreme observations in the actual UIP that effect the MSE more than the MAE. The bottom line is that we find strong support for that our endogenized MS model approach model is efficient in outperforming the naïve constant model.

The Logit Model

From the Logit regression we can see that some currencies yield similar results. For the two carry trade currencies, NZD and AUD, many exogenous variables are the same when trying to predict the regime shifts. Deviations exist in the ISM which have the opposite signs between the two currencies and the GDP that is only significant for the AUD. The signs seem to be somewhat contradictive, as what could be considered bad news for the world economy, such as disappointing GDP for the US predicts the variance to decrease for the AUD while it is unchanged for the NZD. Higher unemployment than expected predicts higher variance for the NZD, but not for the AUD. A reason for these deviations might be that the currencies are usually considered to be similar from an investors' point of view since both are very exposed to the general situation for commodities. Thus some investors might use these two currencies as substitutes to each other, rather than complements. The overall conclusion might be that our model agrees with empirical observations in that both GDP disappointment and a higher than expected unemployment, increase uncertainty in the market causing a higher volatility.

For chain s the intercept is very negative for all currencies, which suggests that ceteris paribus the variable should be close to zero. Further the intercept for chain z is slightly negative but close to zero, suggesting equal expectations for low and high variance. This supports the notion that the most common states will be 2 and 4, and hence the currencies will mostly hop between them. Thus, unless there are no negative surprises from the United States to increase risk aversion in the global economy, traders should be able to continue to enjoy profits from carry trades. On the other hand, if the risk aversion floods the global economy and stemming from either negative surprises in the GDP and ISM or higher than expected unemployment, the most currencies are likely to return to the unpredictable returns in the UIP state.

For the CHF, the variance seems very hard to predict since chain z has no significant variable on the 5% level and only one significant variable on 1%, which is MACD Sell. For the MACD in general, neither Buy nor Sell is significant for any other currency in the sample, except the JPY, which suggests that it is weak in explaining regime shifts. For the CHF a sell signal for the MACD suggests a higher volatility, i.e. chain z has a greater chance of being 1. Moreover, chain s, which is decoupled from the variance and has a positive effect on returns, has two significant variables on the 5% level, GDP and RSI sell. The negative correlation between chain s and large deviations from the GDP suggests that if the economy performs worse than expected, s is more likely to be zero thus and yielding a lower absolute return. Moreover, the RSI has the expected sign since the signal actually predicts that the mean will go down. Combining the results for chain z and s, we see that the CHF is most likely to be in state 2 or 4. Note that state 2 is not the UIP state for this currency, but state 4 is the UIP state instead, since state 2 has a significant negative return while state four does not. Hence we see that the CHF follows an opposite pattern compared to the AUD and NZD, since the UIP state for the CHF is when the markets have low volatility.

In general, except for the EUR, JPY and CHF, it seems like fundamental variables explain z better than they do s, and technical variables explain s better than they do z. Since z controls both the variance and the return it could be argued that fundamental variables indicate that there is a linear relationship between risk and return, while the excess return that is not a compensation for a higher risk seems to be driven more by technical indicators.

Moreover, currencies that have the highest amount of significant coefficients are the CAD, NOK, AUD and NZD. These currencies are all to a great extent connected to commodity prices. It could be that the fundamental variables affect the prices of commodities and that the commodities, in turn, affect these currencies but not the others. However, in the sample these currencies also have the highest minimum variance (λ_0^σ) in the estimated Markov model. Christoffersen and Diebold (2004) suggest in their paper that volatility and volatility persistence is a key component in direction of change forecasting, as long as the expected return is non zero. This could also explain why we find a good fit for some currencies and not others.

We also argue that it is not the magnitude or how many significant variables that is of the greatest importance, but indeed which variables that we find significance for. One key finding is that by looking at what figures and releases that drives the regime shifts, it will be easier for market practitioners to asses the likeliness of an event happening for a specific currency given a certain signal. Hence, we believe that our contribution from this paper is of great importance, especially from a market practitioners' point of view.

The inclusion of technical indicators was further supported by the chi-square model specification test. It showed that in most cases the combined model specification was the model to prefer for both chains z and s. To combine two different models like this might be useful if they prove to be picking up different signals, and thus find completely different investment opportunities. However, it can also yield benefits if they identify different types of risk as well. Hence, we believe that having both fundamental variables and technical indicators in mind when dealing with currencies display traits that could be beneficial for most investors.

The Trading rule

In addition to the econometric performance test, the perhaps more important implication is if this model actually identifies good investment opportunities and that the model is efficient in generating positive returns. As seen from our results, the returns of our model vary for the different currencies, trading filters and model specifications. However, before we make any further inferences it is important to note that our trading model is not earning its average return by being in the market for the entire year. As we see from Appendix 11 we are only in the market for an average of tops one third of the year. This stems from that our model is always waiting for the right opportunity, constantly considering the RR at any given point in time, but only enters the market when our model predicts the RR to be large enough.

To better compare efficiency between our models we followed Bodie et. al. (2005) and performed a modified version of DuPont analysis, which compares average amount of trades per year and average profit per trade, to break down the profit analysis into volume and margin respectively. We account for the trading costs in the model and then annualize the return by dividing the yearly return with the fraction of time the model spends in the market. We do this to mirror how much return per time unit each model makes, and since annual returns are a common benchmark and other theses use it as well it will be more correct for comparison.

By annualizing returns we see that even tough some currencies yield a higher total return per year, we get an entirely different result looking at the efficiency of each trade. The AUD, which has a 5.3% return p.a. using the strictest trading rule, earned that during only 4.5% of the year, or less than two weeks. By adjusting that figure by the time we are out of the market we find that the annualized rate is 124.64%, which would make that currency in general and that trading rule in particular, the most efficient combination out of all our rules and currencies. For the fundamentals we now find that the effective return per year is higher for the two stricter states, than it is for the more loose states, thus meaning that the stricter states are actually more efficient. We cannot stress enough though, that these returns are for comparison purposes only and not expected.

Furthermore, we now see that the technical indicators do not seem to add much return in the trading simulation, as the return is negative for all the rules when using the technicals only model specification. They signal more investment opportunities, but this has not any positive impact on returns. This might be due to that even though the different variables can pick up different signals, they can theoretically yield contradicting signals as well. If the market is affected by a significant positive shock, the fundamental variables will signal to enter the market. However, after a short while with sharply rising return, the technical indicators will probably signal the model to sell, even though the trend is still positive. These contradictory signals can be explained by our warning in the data description for the RSI, where we state that the indicator can stay overbought or oversold for longer periods of time. All this suggests that the technical indicators can be very inefficient to use, and should probably be used sparsely if unmonitored.

Comparing two of our best currencies in terms of trading returns we see that, even though the AUD is more efficient in its trading, our model seems to find better, more persisting opportunities in the NOK making the absolute returns higher.

As a summary we can say that we cannot conclude if our model trades better with higher volume or margins, but we can say that using only fundamental variables in the model specification seems to give the highest efficiency in returns.

7. Conclusions

This paper has investigated if Markov switching regimes can be endogenized, to better help explain movements in the foreign exchange markets. We conclude that the endogenization of the Markov processes indeed can help us understand what lies behind some of the exchange rate movements for a currency pair. Additionally, we find indications that the UIP actually holds for large periods at the time for currencies, and that only a significant impact from some of our exogenous variables can push the currency out of that UIP state. Moreover, this does also mean that the UIP can co-exist with the forward premium puzzle and other UIP anomaly theories without being rejected.

Furthermore, we show that the endogenization process improves if we use a mix of technical and fundamental indicators, where the fundamental variables in our model tend to explain more of the linear returns and the technical indicators explain more of the returns not connected to higher risk. These results fail to carry over to the returns in our trading returns, as the signals from the technical indicators do not seem to be efficient. We find mixed results for various currencies, but overall our out-of-sample trading model creates an average annual return of 2.4%, but with ranges between +19.5% and -5.1%.

However, we also state that this model specification cannot only be used when forecasting currency movements, but we argue that parts of the model can also be implemented when forecasting currency option prices as well.

8. Discussion

A number of issues with our model need to be addressed. We need to say that while we compare our results with Dueker and Neely (2007), we are also aware that their data was on a different and bigger time sample, why returns from trading rules and similar output might not be comparable. Our small sample could also potentially give rise to a small-sample bias. Faust et. al suggests that results are time sensitive so that results obtained might vary across time. However, Dueker and Neely did not find any structural breaks in their Markov model between the centuries, though, suggesting that our returns could be comparable. On the other hand, we have had one of the biggest crises in modern history which even resulted in that in December of 2009 the over night interest rates were negative for a short period of time. The crisis has even changed some of the literature on economics, which definitely could suggest a structural break in the model. That would, in turn, mean that our data could be biased, thus creating a Peso problem which we in our model assume we have not. However, as the economic climate was in a recession in the beginning of the millennium as well, we believe that the crisis will not lead to any significant biases in our later estimations.

Another difference between the Dueker and Neely paper is that we have chosen to only look at the two first moments, mean and variance, whereas they have also looked at the kurtosis. Given that this might be a simplification, but we believe this alteration is sufficient for our purposes since we are merely trying to describe the data, not make any predictions at this point. We furthermore believe this change is a fair deviation from their model, since we take the timing of the releases into account later in the paper when we perform the Logit regression.

MS models have also been used as an alternative way to forecast interest rates as in Ang and Bekaertz (2002b) where they produce better results than an affine multi-factor model. As we realize that this could be a useful application for our model, since interest rates are included in the UIP, we also realize that this is outside the scope of this paper.

Another issue is if the Bloomberg forecasts can be said to mirror the market expectations. However, there is usually a plethora of forecasts for these variables in the Bloomberg estimates, sometimes exceeding estimates from over 50 forecasters from main banks around the globe, and thus it can be argued that this measure provides a fair picture of the expectations for the market as a whole.

For further research it would be interesting to look at if higher moments could help explain the model better, and at the same time use a multivariate Logit regression to infer relationships between the variables. Also, using other exogenous variables, like the VIX index, and oil prices when doing the Logit analysis could furthermore be interesting, as different variables affect will not always react the same in times of crises. Other variables that might be worth considering is the impact from national variables and how they relate to the US market data.

In the analysis we also bring up the question if spatial distance between a traded currency pair matter for the predictive ability. This could also prove to be an interesting topic for future research.

Lastly, we would like to point out that we in this paper do not try to specify a water proof trading model or trading rule, but we rather try to show how the underlying concepts of endogenization can be used as a complement to assist market practitioners in their daily work.

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10.Appendices

Appendix 1

Currency returns

	EUR	JPY	GBP	CHF	CAD	AUD	NZD	SEK	NOK
Mean	0,0002	0,0001	0,0000	0,0002	0,0002	0,0002	0,0001	0,0001	0,0002
Median	0,0002	-0,0001	0,0001	-0,0001	0,0002	0,0004	0,0005	0,0001	0,0002
Standard Deviation	0,0064	0,0065	0,0062	0,0069	0,0060	0,0087	0,0089	0,0080	0,0082
Sample Variance	0,0000	0,0000	0,0000	0,0000	0,0000	0,0001	0,0001	0,0001	0,0001
Kurtosis	2,2253	3,6658	4,7306	2,3742	6,2078	11,8785	5,1559	4,2153	13,5885
Skewness	0,1662	0,4824	-0,0315	0,2319	0,2954	-0,8109	-0,4485	0,3641	0,3418
Range	0,0657	0,0781	0,0876	0,0808	0,0932	0,1602	0,1281	0,0963	0,1763
Minimum	-0,0264	-0,0282	-0,0352	-0,0268	-0,0353	-0,0909	-0,0635	-0,0310	-0,0823
Maximum	0,0393	0,0500	0,0524	0,0540	0,0578	0,0693	0,0646	0,0653	0,0940
Sum	0,3995	0,1597	-0,0131	0,4739	0,3990	0,4473	0,3715	0,2223	0,4202
Count	2601	2601	2601	2601	2601	2601	2601	2601	2601
JB	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

Interest Rate Differentials

	EUR	JPY	GBP	CHF	CAD	AUD	NZD	SEK	NOK
Mean	0,0000	-0,0001	0,0001	-0,0001	0,0000	0,0001	0,0001	0,0000	0,0001
Median	0,0000	-0,0001	0,0000	0,0000	0,0000	0,0001	0,0001	0,0000	0,0000
Standard Deviation	0,0001	0,0001	0,0001	0,0001	0,0000	0,0001	0,0001	0,0001	0,0001
Sample Variance	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Kurtosis	1,9729	4,3072	3,0432	4,3708	2,7883	3,2460	4,5922	1,8233	3,0998
Skewness	-0,0987	-1,9650	1,5299	-1,9670	0,9039	1,6527	1,8897	0,0996	1,3688
Range	0,0006	0,0006	0,0006	0,0005	0,0003	0,0006	0,0007	0,0008	0,0008
Minimum	-0,0002	-0,0006	-0,0002	-0,0004	-0,0001	-0,0001	-0,0001	-0,0002	-0,0002
Maximum	0,0003	0,0000	0,0004	0,0001	0,0002	0,0005	0,0007	0,0005	0,0007
Sum	0,0125	-0,2608	0,1430	-0,1557	0,0293	0,2247	0,3156	0,0197	0,1727
Count	2601	2601	2601	2601	2601	2601	2601	2601	2601
JB	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

Appendix 2

Appendix 1 summarizes the correlations 1) between the different interest rates and 2) between the interest rates.

Correlations Currencies/Interest Rates

Currency Correlations

	EUR	JPY	GBP	CHF	CAD	AUD	NZD	SEK	NOK
EUR	1,00	0,29	0,68	0,90	0,47	0,59	0,57	0,84	0,79
JPY	0,29	1,00	0,17	0,42	0,01	0,01	0,02	0,17	0,18
GBP	0,68	0,17	1,00	0,60	0,45	0,54	0,54	0,61	0,61
CHF	0,90	0,42	0,60	1,00	0,35	0,44	0,44	0,73	0,70
CAD	0,47	0,01	0,45	0,35	1,00	0,59	0,53	0,50	0,46
AUD	0,59	0,01	0,54	0,44	0,59	1,00	0,83	0,60	0,56
NZD	0,57	0,02	0,54	0,44	0,53	0,83	1,00	0,57	0,53
SEK	0,84	0,17	0,61	0,73	0,50	0,60	0,57	1,00	0,78
NOK	0,79	0,18	0,61	0,70	0,46	0,56	0,53	0,78	1,00

Interest Rate Correlations

	EUR	JPY	GBP	CHF	CAD	AUD	NZD	SEK	NOK
EUR	1,00	0,64	0,70	0,77	0,88	0,64	0,51	0,98	0,85
JPY	0,64	1,00	0,18	0,90	0,51	0,24	-0,02	0,63	0,25
GBP	0,70	0,18	1,00	0,23	0,75	0,81	0,82	0,73	0,63
CHF	0,77	0,90	0,23	1,00	0,58	0,21	-0,04	0,72	0,46
CAD	0,88	0,51	0,75	0,58	1,00	0,68	0,56	0,90	0,76
AUD	0,64	0,24	0,81	0,21	0,68	1,00	0,90	0,66	0,57
NZD	0,51	-0,02	0,82	-0,04	0,56	0,90	1,00	0,53	0,50
SEK	0,98	0,63	0,73	0,72	0,90	0,66	0,53	1,00	0,84
NOK	0,85	0,25	0,63	0,46	0,76	0,57	0,50	0,84	1,00

Appendix 3

This table summarizes the Dicker-Fuller test for a Unit root process.

Currency	Reject H0	Test-statistic	Critical Value
EUR	Yes	-46,2353	-3,4143
JPY	Yes	-46,3488	-3,4143
GBP	Yes	-44,7086	-3,4143
CHF	Yes	-47,9646	-3,4143
CAD	Yes	-46,5027	-3,4143
AUD	Yes	-43,6158	-3,4143
NZD	Yes	-43,1001	-3,4143
SEK	Yes	-44,7900	-3,4143
NOK	Yes	-43,9908	-3,4143

Appendix 4

This table show descriptive statistics of all fundamental variables. Graphs can be found on next page.

Descriptive Statistics Fundamental Variables

GDP

	Actual Release	*Survey Average*	*Deviation*
Mean	2,25	2,29	-0,04
Median	2,55	2,82	0,00
Standard Deviation	2,84	2,89	0,29
Sample Variance	8,09	8,37	0,09
Kurtosis	2,49	2,67	1,48
Skewness	-1,05	-1,16	-0,88
Range	14,50	14,78	1,42
Minimum	-6,30	-6,55	-0,94
Maximum	8,20	8,23	0,48
Sum	80,90	82,42	-1,52
Count	36	36	36
JB Test	0,03	0,02	0,02

NFP

	Actual Release	*Survey Average*	*Deviation*
Mean	5,82	5,84	-0,02
Median	5,50	5,43	-0,02
Standard Deviation	1,54	1,54	0,15
Sample Variance	2,38	2,37	0,02
Kurtosis	1,88	1,99	-0,04
Skewness	1,67	1,70	0,24
Range	6,00	6,09	0,72
Minimum	4,20	4,11	-0,34
Maximum	10,20	10,20	0,38
Sum	646,00	647,78	-1,78
Count	111	111	111
JB Test	0,00	0,00	0,00

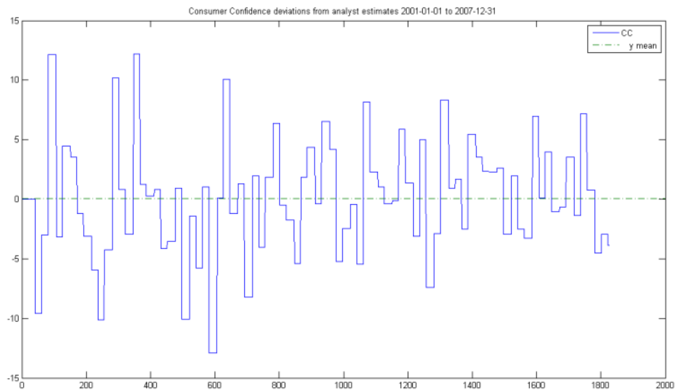
CC

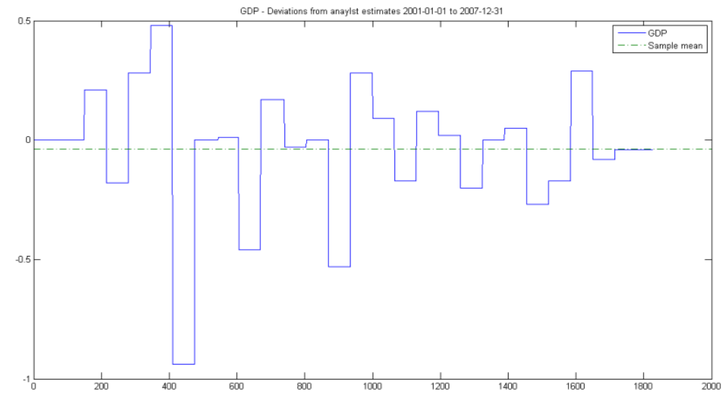
	Actual Release	*Survey Average*	*Deviation*
Mean	86,45	86,69	-0,23
Median	93,50	94,14	0,03
Standard Deviation	23,58	22,76	5,30
Sample Variance	555,86	517,85	28,13
Kurtosis	-0,37	-0,25	0,11
Skewness	-0,86	-0,91	0,03
Range	92,90	96,25	26,03
Minimum	25,00	27,71	-13,70
Maximum	117,90	123,96	12,33
Sum	9596,40	9622,46	-26,06
Count	111	111	111
JB Test	0,00	0,00	0,00

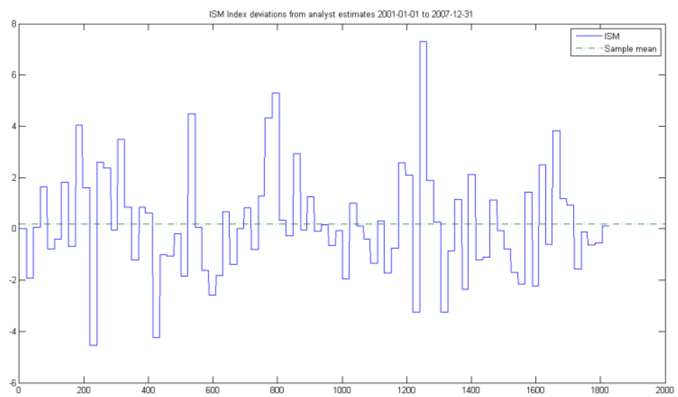
ISM

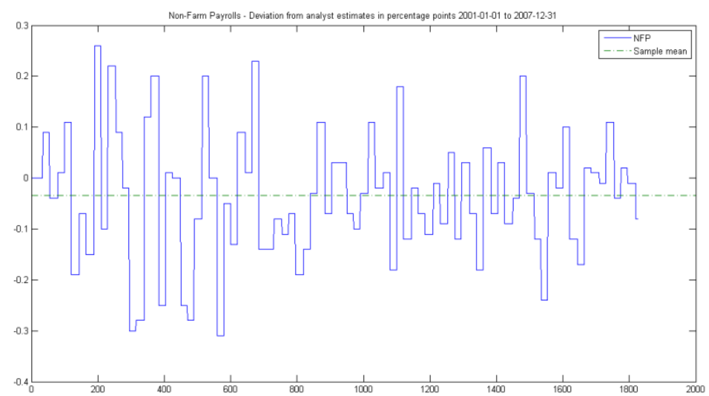
	Actual Release	*Survey Average*	*Deviation*
Mean	51,71	51,46	0,25
Median	52,90	52,11	0,11
Standard Deviation	6,65	6,37	2,10
Sample Variance	44,18	40,63	4,39
Kurtosis	0,34	0,49	0,91
Skewness	-0,58	-0,75	0,20
Range	33,80	30,60	13,17
Minimum	32,40	32,67	-5,87
Maximum	66,20	63,27	7,30
Sum	5739,50	5711,59	27,91
Count	111	111	111
JB Test	0,00	0,00	0,00

Graphs over deviations from analyst estimates for each of our fundamental variables.









Appendix 5

The table shows summary statistics for the UIP variable. The data spans from May 2000 to April 2010

UIP Deviations

	EUR	*JPY*	*GBP*	*CHF*	*CAD*	*AUD*	*NZD*	*SEK*	*NOK*
Mean	0,0002	-0,0001	0,0002	0,0001	0,0002	0,0003	0,0003	0,0002	0,0003
Standard Deviation	0,0059	0,0058	0,0051	0,0064	0,0048	0,0069	0,0076	0,0066	0,0065
Sample Variance	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0001	0,0000	0,0000
Kurtosis	0,8743	2,8806	0,6566	0,7857	1,2232	2,7610	3,6928	0,5495	0,5496
Skewness	-0,0810	0,4415	-0,0783	0,0128	-0,1142	-0,5521	-0,6602	-0,0871	-0,1588
Minimum	-0,0243	-0,0247	-0,0196	-0,0241	-0,0255	-0,0481	-0,0619	-0,0301	-0,0252
Maximum	0,0236	0,0452	0,0212	0,0276	0,0172	0,0303	0,0324	0,0218	0,0222
Sum	0,4746	-0,2712	0,3493	0,2664	0,4220	0,5344	0,6669	0,3199	0,6116
Count	2601	2601	2601	2601	2601	2601	2601	2601	2601
JB Test	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00

Appendix 6

The table shows summary statistics for all our technical indicators in sample. The out of sample statistics can be found on next page.

Descriptive Statistics of Technical Indicators (In sample)

Relative Strength Index (RSI)

	EUR	*JPY*	*GBP*	*CHF*	*CAD*	*AUD*	*NZD*	*SEK*	*NOK*
# Buy signals	368	286	335	290	303	364	407	330	365
Avg time between Buy signal	4,96	6,38	5,45	6,29	6,02	5,01	4,48	5,53	5,00
# Sell signals	160	234	180	179	170	134	127	169	162
Avg time between Sell signal	11,41	7,80	10,14	10,20	10,74	13,62	14,37	10,80	11,27
Total # of signals	528	520	515	469	473	498	534	499	527
Avg time between signal	3,46	3,51	3,54	3,89	3,86	3,66	3,42	3,66	3,46

MACD

	EUR	*JPY*	*GBP*	*CHF*	*CAD*	*AUD*	*NZD*	*SEK*	*NOK*
# Buy signals	64	67	66	70	69	72	71	38	78
Avg time between Buy signal	28,52	27,24	27,65	26,07	26,45	25,35	25,70	48,03	23,40
# Sell signals	63	67	65	70	70	72	71	39	77
Avg time between Sell signal	28,97	27,24	28,08	26,07	26,07	25,35	25,70	46,79	23,70
Total # of signals	127	134	131	140	139	144	142	77	155
Avg time between signal	14,37	13,62	13,93	13,04	13,13	12,67	12,85	23,70	11,77

Stochastics (%D/%K)

	EUR	*JPY*	*GBP*	*CHF*	*CAD*	*AUD*	*NZD*	*SEK*	*NOK*
# Buy signals	76	126	81	76	85	74	55	74	85
Avg time between Buy signal	24,01	14,48	22,53	24,01	21,47	24,66	33,18	24,66	21,47
# Sell signals	126	97	119	114	142	147	136	132	123
Avg time between Sell signal	14,48	18,81	15,34	16,01	12,85	12,41	13,42	13,83	14,84
Total # of signals	202	223	200	190	227	221	191	206	208
Avg time between signal	9,03	8,18	9,13	9,61	8,04	8,26	9,55	8,86	8,77

Descriptive Statistics of Technical Variables (Out of sample)

Relative Strength Index (RSI)

	EUR	*JPY*	*GBP*	*CHF*	*CAD*	*AUD*	*NZD*	*SEK*	*NOK*
# Buy signals	73	58	46	72	62	95	70	60	71
Avg time between Buy signal	8,26	10,40	13,11	8,38	9,73	6,35	8,61	10,05	8,49
# Sell signals	85	83	103	71	68	59	69	63	49
Avg time between Sell signal	7,09	7,27	5,85	8,49	8,87	10,22	8,74	9,57	12,31
Total # of signals	158	141	149	143	130	154	139	123	120
Avg time between signal	3,82	4,28	4,05	4,22	4,64	3,92	4,34	4,90	5,03

MACD

	EUR	*JPY*	*GBP*	*CHF*	*CAD*	*AUD*	*NZD*	*SEK*	*NOK*
# Buy signals	19	22	22	20	22	21	25	14	23
Avg time between Buy signal	31,74	27,41	27,41	30,15	27,41	28,71	24,12	43,07	26,22
# Sell signals	20	21	23	20	22	22	25	13	24
Avg time between Sell signal	30,15	28,71	26,22	30,15	27,41	27,41	24,12	46,38	25,13
Total # of signals	39	43	45	40	44	43	50	27	47
Avg time between signal	15,46	14,02	13,40	15,08	13,70	14,02	12,06	22,33	12,83

Stochastics (%D/%K)

	EUR	*JPY*	*GBP*	*CHF*	*CAD*	*AUD*	*NZD*	*SEK*	*NOK*
# Buy signals	28	32	37	33	31	23	26	37	30
Avg time between Buy signal	21,54	18,84	16,30	18,27	19,45	26,22	23,19	16,30	20,10
# Sell signals	25	35	29	28	38	46	31	30	35
Avg time between Sell signal	24,12	17,23	20,79	21,54	15,87	13,11	19,45	20,10	17,23
Total # of signals	53	67	66	61	69	69	57	67	65
Avg time between signal	11,38	9,00	9,14	9,89	8,74	8,74	10,58	9,00	9,28

Appendix 7

EUR/USD

ESTIMATED PARAMETERS

	Starting Value	Lower Bound	Upper Bound	Estimation	Standard Error	P-value
sigma0	0,000017	0,00E+00	0,00060	0,000007	0,000002	0,0011
sigma1	0,000035	0,00E+00	0,00060	0,000030	0,000004	0,0000
Lambda0	0,000000	-0,02426	0,02363	-0,000432	0,000296	0,1454
Lambda1	0,000238	-0,02426	0,02363	0,001760	0,000965	0,0683
Lambda2	0,000119	-0,02426	0,02363	-0,009319	0,001171	0,0000
pz11	0,900000	0	1	0,658936	0,123554	0,0000
pz22	0,900000	0	1	0,076851	0,156284	0,6230
ps11	0,900000	0	1	0,096372	0,083287	0,2474
ps22	0,900000	0	1	0,936141	0,050131	0,0000

Transiton Matrix For Z		Transiton Matrix For S	
0,6589	0,9231	0,0964	0,0639
0,3411	0,0769	0,9036	0,9361

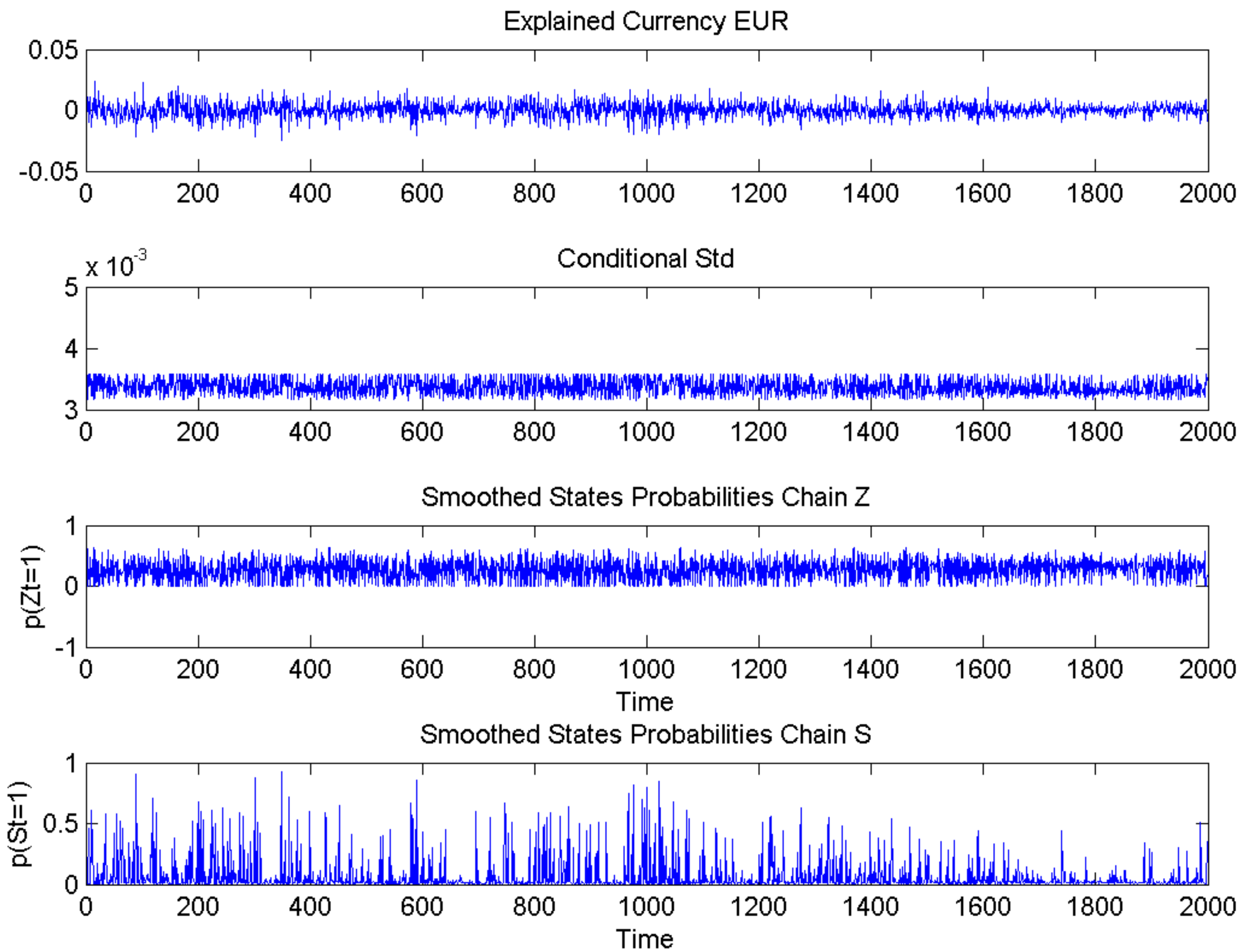
	Long term average	Threshold
p(z=1)	0,7302	0,5752
p(s=1)	0,0660	0,5000

ESTIMATED MODEL

		Value	Standard Error	P-Value	State Label
State 1	*Deviation*	-0,007990	0,0015462	0,0000	
	Variance	0,000037	4,664E-06	0,0000	
State 2	*Deviation*	0,001329	0,0010094	0,1883	
	Variance	0,000037	4,664E-06	0,0000	
State 3	*Deviation*	-0,009750	0,0012082	0,0000	
	Variance	0,000007	2,042E-06	0,0011	
State 4	*Deviation*	-0,000432	0,000296	0,1454	
	Variance	0,000007	2,042E-06	0,0011	

Average Duration of regimes (Days)	
pz11	1,93
pz22	0,08
ps11	0,11
ps22	14,66

Testing the Markov Model	In Sample	Out of Sample
(Fund & Tech)		
MAE	0,9997	0,9976
MSE	0,9996	0,9986
% Right	0,5180	0,5124
(Tech)		
MAE		0,9976
MSE		0,9987
% Right		0,5124
(Fund)		
MAE		0,9977
MSE		0,9984
% Right		0,5124


Explained Currency EUR
0.05
0
-0.05
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Conditional Std
x 10-3
5
4
3
Smoothed States Probabilities Chain Z
p(Zt=1)
1
0
-1
Time
Smoothed States Probabilities Chain S
p(St=1)
1
0.5
0
Time

JPY/USD

ESTIMATED PARAMETERS

	Starting Value	Lower Bound	Upper Bound	Estimation	Standard Error	P-value
sigma0	0,000015	0,00E+00	0,00038	0,000006	0,000002	0,0005
sigma1	0,000031	0,00E+00	0,00038	0,000025	0,000003	0,0000
Lambda0	-0,000219	-0,01937	0,01932	-0,000815	0,000302	0,0070
Lambda1	0,000219	-0,01937	0,01932	0,002218	0,000781	0,0046
Lambda2	-0,000219	-0,01937	0,01932	-0,006851	0,000750	0,0000
pz11	0,900000	0	1	0,774234	0,087917	0,0000
pz22	0,900000	0	1	0,436622	0,134971	0,0012
ps11	0,900000	0	1	0,034265	0,103231	0,7400
ps22	0,900000	0	1	0,836526	0,051019	0,0000

Transiton Matrix For Z		Transiton Matrix For S	
0,7742	0,5634	0,0343	0,1635
0,2258	0,4366	0,9657	0,8365

	Long term average	Threshold
p(z=1)	0,7139	0,5741
p(s=1)	0,1448	0,4933

ESTIMATED MODEL

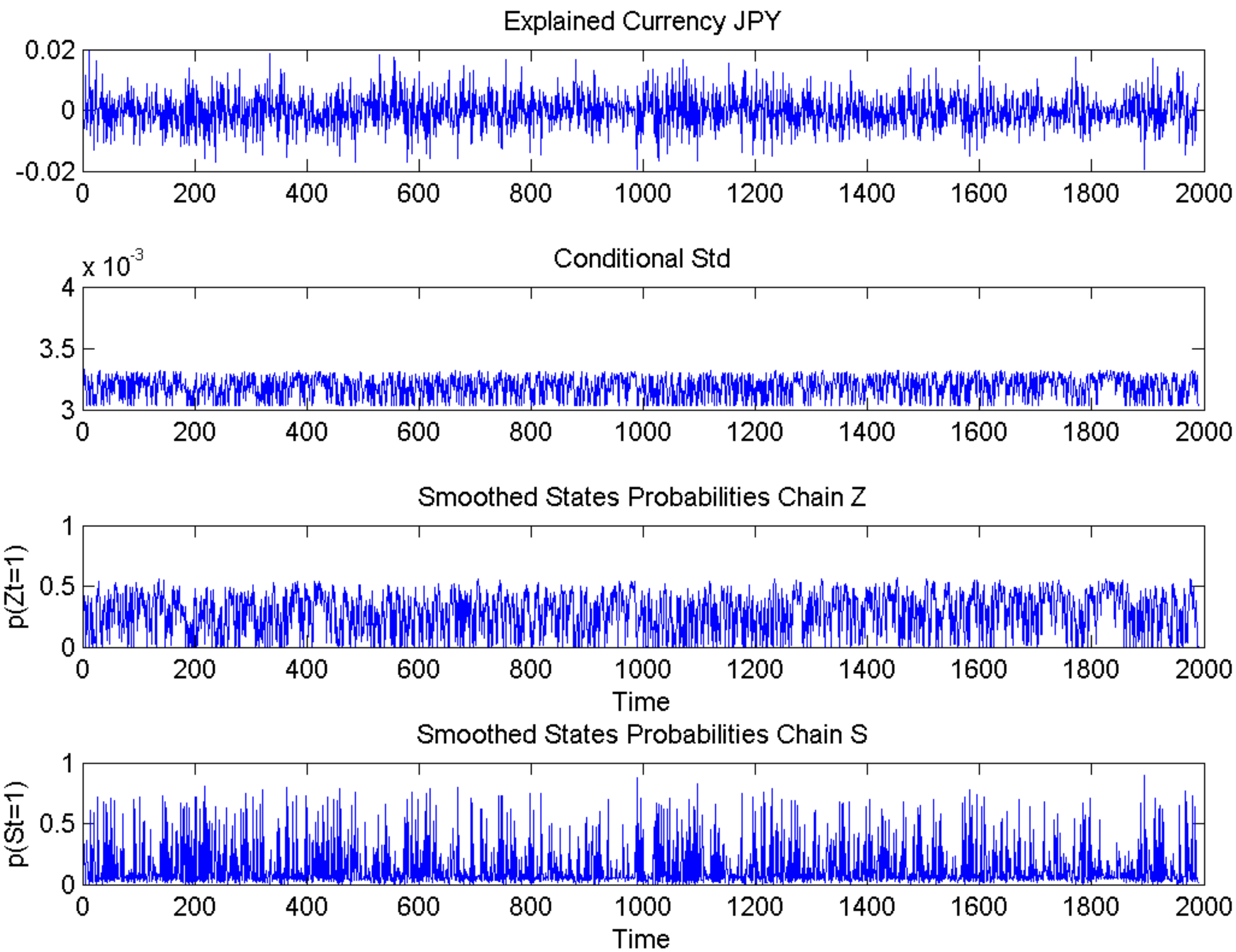
		Value	Standard Error	P-Value	State Label
State 1	*Deviation*	-0,005448	0,0011246	0,0000	
	Variance	0,000031	3,643E-06	0,0000	
State 2	*Deviation*	0,001403	0,0008377	0,0942	
	Variance	0,000031	3,643E-06	0,0000	
State 3	*Deviation*	-0,007667	0,0008088	0,0000	
	Variance	0,000006	1,711E-06	0,0005	
State 4	*Deviation*	-0,000815	0,000302	0,0070	
	Variance	0,000006	1,711E-06	0,0005	

Average Duration of regimes (Days)

pz11	3,43
pz22	0,78
ps11	0,04
ps22	5,12

Testing the Markov Model

(Fund & Tech)		
MAE	0,9995	1,0083
MSE	1,0004	1,0151
% Right	0,5286	0,4959
(Tech)		
MAE		1,0072
MSE		1,0128
% Right		0,4959
(Fund)		
MAE		1,0070
MSE		1,0130
% Right		0,4959



Explained Currency JPY
0.02
0
-0.02
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Conditional Std
x 10^-3
4
3.5
3
Smoothed States Probabilities Chain Z
p(Zt=1)
1
0.5
0
Time
Smoothed States Probabilities Chain S
p(St=1)
Time

GBP/USD

ESTIMATED PARAMETERS

	Starting Value	Lower Bound	Upper Bound	Estimation	Standard Error	P-value
sigma0	0,000012	0,00E+00	0,00030	0,000009	0,000001	0,0000
sigma1	0,000025	0,00E+00	0,00030	0,000016	0,000001	0,0000
Lambda0	0,000096	-0,01647	0,01752	0,000807	0,000271	0,0029
Lambda1	0,000193	-0,01647	0,01752	-0,000265	0,000271	0,3288
Lambda2	0,000193	-0,01647	0,01752	-0,007287	0,001563	0,0000
pz11	0,900000	0	1	0,998047	0,001412	0,0000
pz22	0,900000	0	1	0,987335	0,007919	0,0000
ps11	0,900000	0	1	0,249067	0,127033	0,0501
ps22	0,900000	0	1	0,959361	0,032249	0,0000

Transiton Matrix For Z		Transiton Matrix For S	
0,9980	0,0127	0,2491	0,0406
0,0020	0,9873	0,7509	0,9594

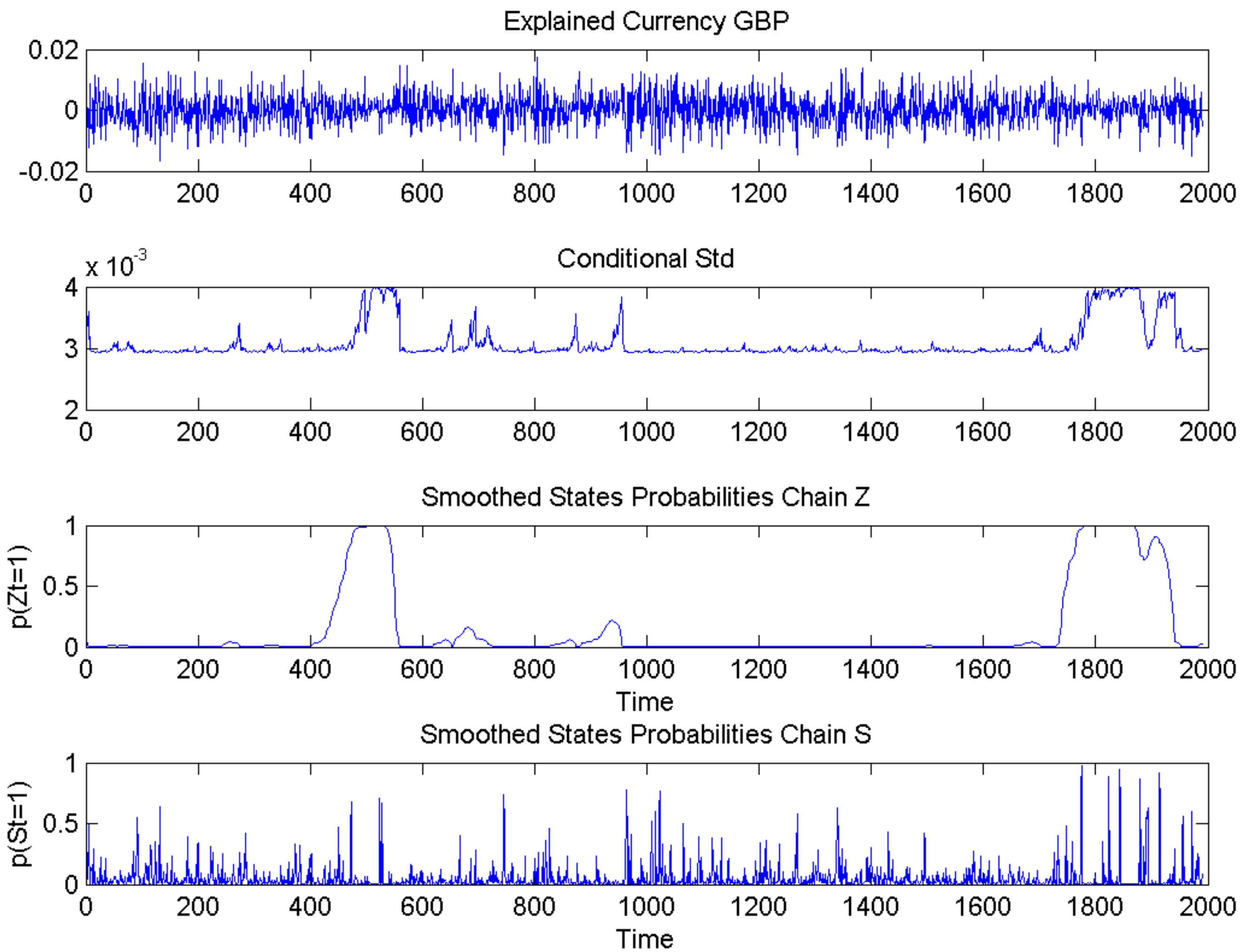
	Long term average	Threshold
p(z=1)	0,8664	0,5000
p(s=1)	0,0513	0,5000

ESTIMATED MODEL

		Value	Standard Error	P-Value	State Label
State 1	*Deviation*	-0,006744	0,0016089	0,0000	
	Variance	0,000025	1,863E-06	0,0000	
State 2	*Deviation*	0,000543	0,0003832	0,1568	
	Variance	0,000025	1,863E-06	0,0000	
State 3	*Deviation*	-0,006480	0,0015859	0,0000	
	Variance	0,000009	1,150E-06	0,0000	
State 4	*Deviation*	0,000807	0,000271	0,0029	
	Variance	0,000009	1,150E-06	0,0000	

Average Duration of regimes (Days)	
pz11	511,12
pz22	77,96
ps11	0,33
ps22	23,61

Testing the Markov Model	In Sample	Out of Sample
(Fund & Tech)		
MAE	0,9989	0,9975
MSE	0,9983	0,9967
% Right	0,5221	0,5357
(Tech)		
MAE		0,9977
MSE		0,9974
% Right		0,5489
(Fund)		
MAE		0,9979
MSE		0,9967
% Right		0,5456



Explained Currency GBP
0.02
0
-0.02
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Conditional Std
x 10-3
4
3
2
Smoothed States Probabilities Chain Z
p(Zt=1)
1
0.5
0
Time
Smoothed States Probabilities Chain S
p(St=1)
Time

CHF/USD

ESTIMATED PARAMETERS

	Starting Value	Lower Bound	Upper Bound	Estimation	Standard Error	P-value
sigma0	0,000019	0,00E+00	0,00043	0,000010	0,000002	0,0000
sigma1	0,000039	0,00E+00	0,00043	0,000029	0,000004	0,0000
Lambda0	0,000157	-0,02059	0,01998	-0,000468	0,000259	0,0714
Lambda1	-0,000157	-0,02059	0,01998	-0,002476	0,000686	0,0003
Lambda2	0,000157	-0,02059	0,01998	0,008731	0,000393	0,0000
pz11	0,900000	0	1	0,299983	0,122981	0,0148
pz22	0,900000	0	1	0,319342	0,148809	0,0320
ps11	0,900000	0	1	0,125788	0,044901	0,0051
ps22	0,900000	0	1	0,764740	0,027860	0,0000

Transiton Matrix For Z		Transiton Matrix For S	
0,3000	0,6807	0,1258	0,2353
0,7000	0,3193	0,8742	0,7647

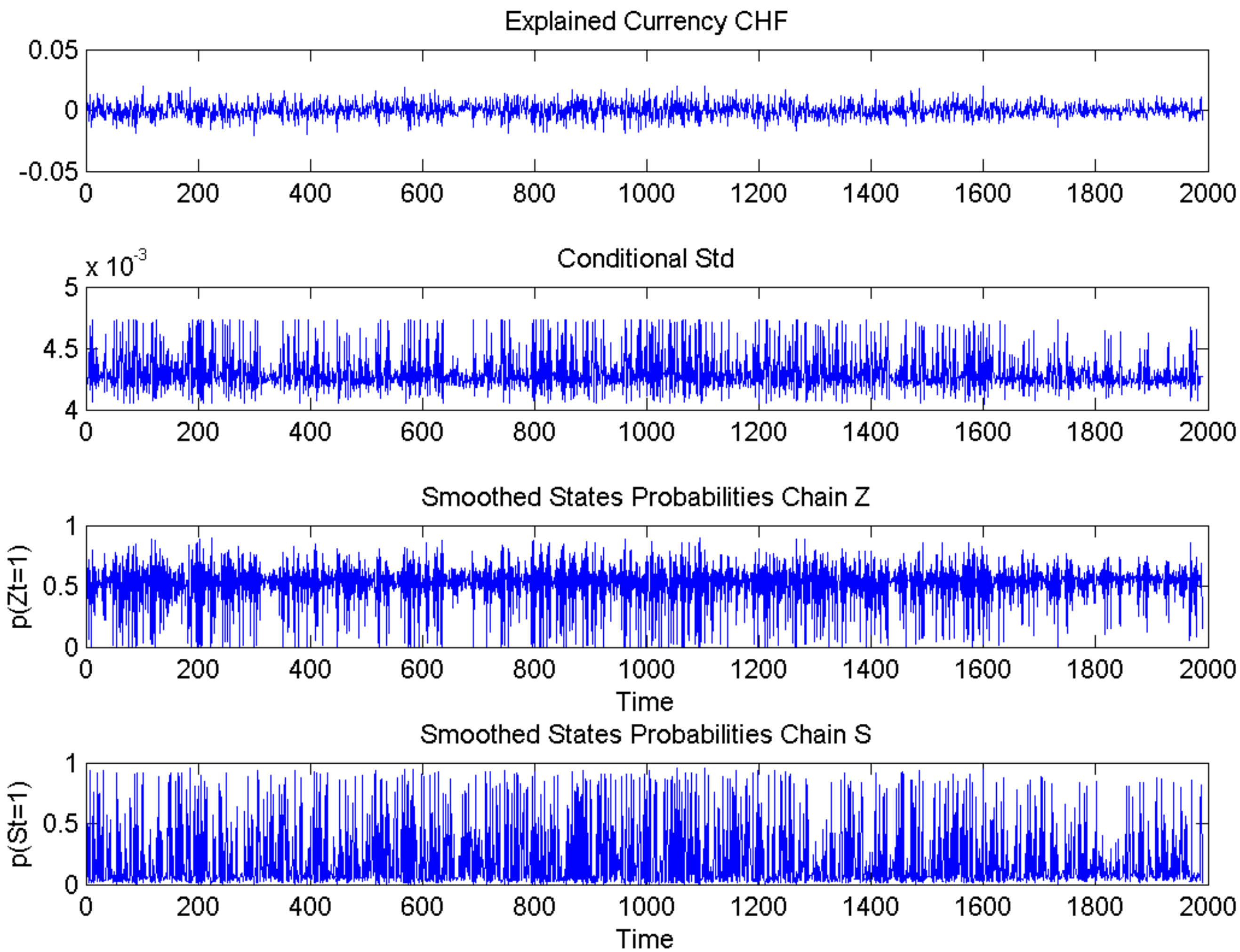
	Long term average	Threshold
p(z=1)	0,4930	0,4723
p(s=1)	0,2120	0,5000

ESTIMATED MODEL

		Value	Standard Error	P-Value	State Label
State 1	*Deviation*	0,005788	0,0008325	0,0000	
	Variance	0,000039	4,228E-06	0,0000	
State 2	*Deviation*	-0,002944	0,0007337	0,0001	
	Variance	0,000039	4,228E-06	0,0000	
State 3	*Deviation*	0,008263	0,0004711	0,0000	
	Variance	0,000010	1,653E-06	0,0000	
State 4	*Deviation*	-0,000468	0,000259	0,0714	
	Variance	0,000010	1,653E-06	0,0000	

Average Duration of regimes (Days)	
pz11	0,43
pz22	0,47
ps11	0,14
ps22	3,25

Testing the Markov Model	In Sample	Out of Sample
(Fund & Tech)		
MAE	0,9978	0,9972
MSE	0,9959	0,9985
% Right	0,5095	0,5058
(Tech)		
MAE		0,9972
MSE		0,9984
% Right		0,5058
(Fund)		
MAE		0,9993
MSE		1,0001
% Right		0,5091



Explained Currency CHF
0.05
0
-0.05
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Conditional Std
x 10^-3
5
4.5
4
Smoothed States Probabilities Chain Z
p(Zt=1)
1
0.5
0
Time
Smoothed States Probabilities Chain S
p(St=1)
1
0.5
0
Time

CAD/USD

ESTIMATED PARAMETERS

	Starting Value	Lower Bound	Upper Bound	Estimation	Standard Error	P-value
sigma0	0,000011	0,00E+00	0,00024	0,000011	0,000001	0,0000
sigma1	0,000021	0,00E+00	0,00024	0,000019	0,000002	0,0000
Lambda0	0,000236	-0,01519	0,01575	0,000229	0,000529	0,6651
Lambda1	-0,000236	-0,01519	0,01575	0,000434	0,000205	0,0347
Lambda2	0,000236	-0,01519	0,01575	-0,004333	0,003955	0,2734
pz11	0,900000	0	1	0,995907	0,002503	0,0000
pz22	0,900000	0	1	0,994528	0,002424	0,0000
ps11	0,900000	0	1	0,095476	0,261465	0,7150
ps22	0,900000	0	1	0,952364	0,153897	0,0000

Transiton Matrix For Z		Transiton Matrix For S	
0,9959	0,0055	0,0955	0,0476
0,0041	0,9945	0,9045	0,9524

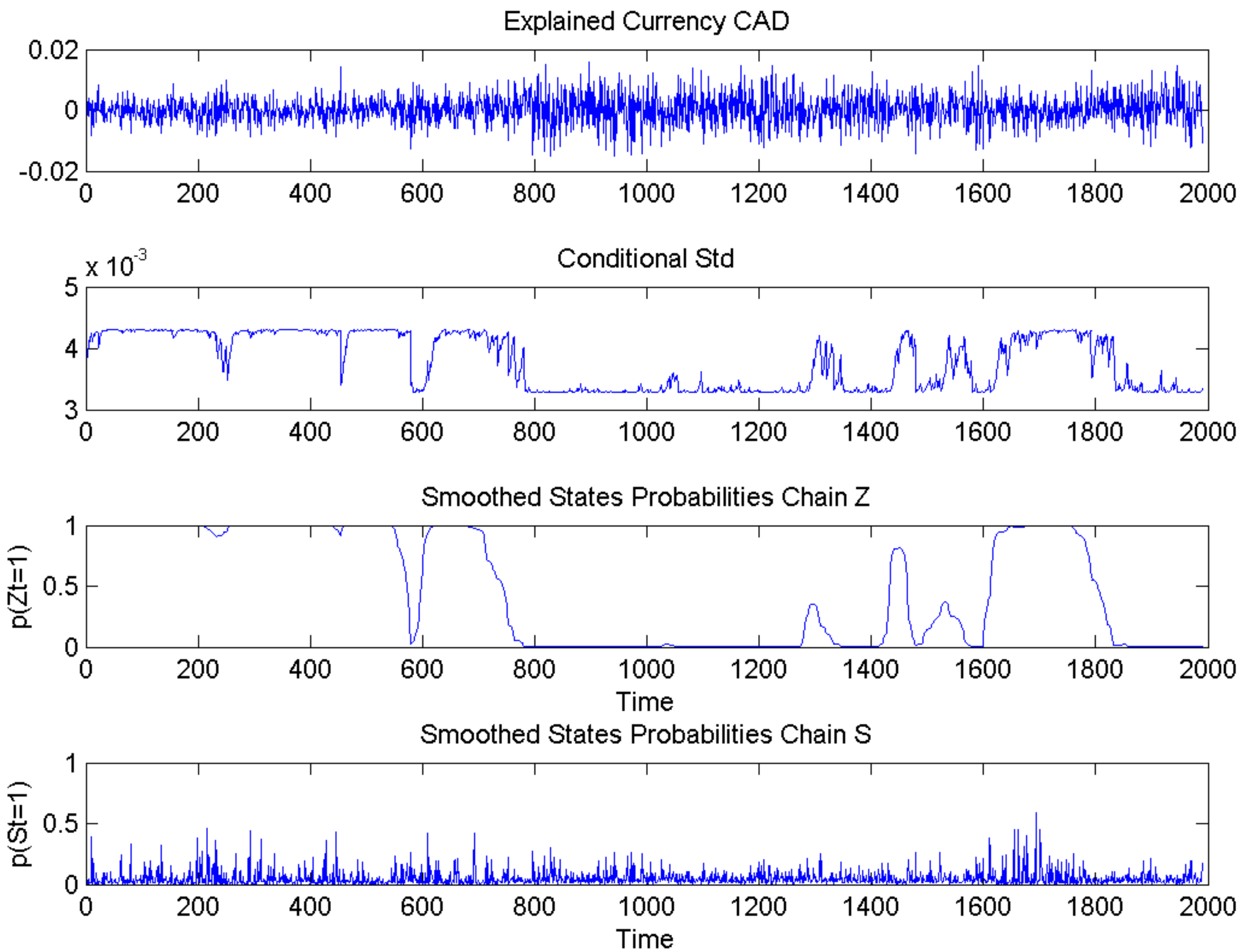
	Long term average	Threshold
p(z=1)	0,5721	0,5000
p(s=1)	0,0500	0,5000

ESTIMATED MODEL

		Value	Standard Error	P-Value	State Label
State 1	*Deviation*	-0,003670	0,0039951	0,3584	
	Variance	0,000029	2,076E-06	0,0000	
State 2	*Deviation*	0,000663	0,0005674	0,2429	
	Variance	0,000029	2,076E-06	0,0000	
State 3	*Deviation*	-0,004104	0,0039898	0,3038	
	Variance	0,000011	1,406E-06	0,0000	
State 4	*Deviation*	0,000229	0,000529	0,6651	
	Variance	0,000011	1,406E-06	0,0000	

Average Duration of regimes (Days)	
pz11	243,31
pz22	181,76
ps11	0,11
ps22	19,99

Testing the Markov Model	In Sample	Out of Sample
(Fund & Tech)		
MAE	0,9989	0,9996
MSE	0,9984	0,9994
% Right	0,5241	0,0000
(Tech)		
MAE		0,9996
MSE		0,9994
% Right		0,0000
(Fund)		
MAE		0,9996
MSE		0,9994
% Right		0,0000



Explained Currency CAD
0.02
0
-0.02
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Conditional Std
x 10^-3
5
4
3
Smoothed States Probabilities Chain Z
p(Zt=1)
1
0.5
0
Time
Smoothed States Probabilities Chain S
p(St=1)
Time

AUD/USD

ESTIMATED PARAMETERS

	Starting Value	Lower Bound	Upper Bound	Estimation	Standard Error	P-value
sigma0	0,000043	0,00E+00	0,00079	0,000025	0,000001	0,0000
sigma1	0,000022	0,00E+00	0,00079	0,000033	0,000003	0,0000
Lambda0	0,000369	-0,02774	0,02737	0,000689	0,000178	0,0001
Lambda1	-0,000369	-0,02774	0,02737	-0,000418	0,000329	0,2041
Lambda2	0,000369	-0,02774	0,02737	-0,017864	0,005948	0,0027
pz11	0,900000	0	1	0,992692	0,003698	0,0000
pz22	0,900000	0	1	0,993246	0,003342	0,0000
ps11	0,900000	0	1	0,239997	0,177680	0,1770
ps22	0,900000	0	1	0,995242	0,004365	0,0000

Transiton Matrix For Z		Transiton Matrix For S	
0,9927	0,0068	0,2400	0,0048
0,0073	0,9932	0,7600	0,9952

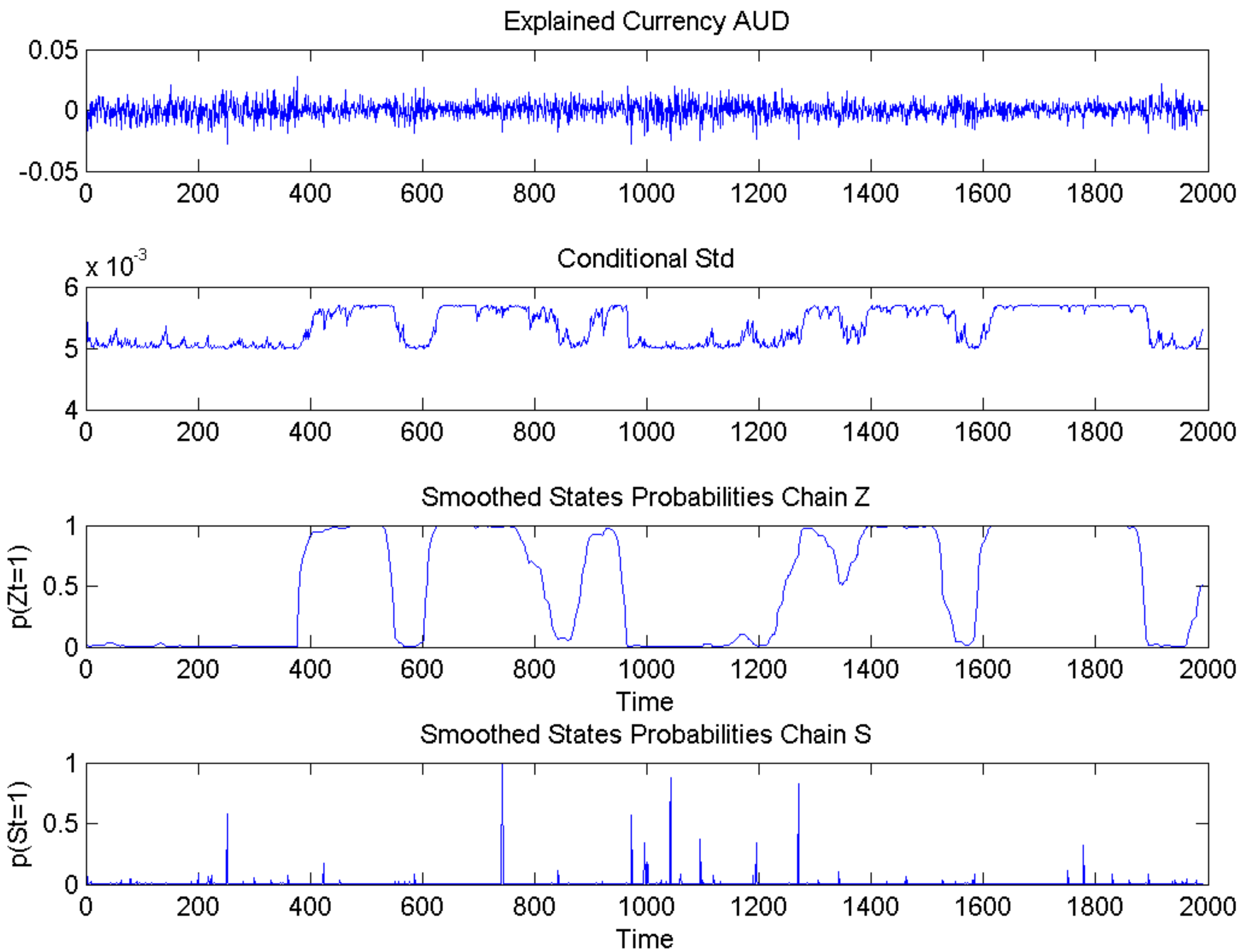
	Long term average	Threshold
p(z=1)	0,4803	0,5000
p(s=1)	0,0062	0,5000

ESTIMATED MODEL

		Value	Standard Error	P-Value	State Label
State 1	*Deviation*	-0,017593	0,0059599	0,0032	
	Variance	0,000058	3,699E-06	0,0000	
State 2	*Deviation*	0,000271	0,0003744	0,4692	
	Variance	0,000058	3,699E-06	0,0000	
State 3	*Deviation*	-0,017174	0,0059508	0,0039	
	Variance	0,000025	1,397E-06	0,0000	
State 4	*Deviation*	0,000689	0,000178	0,0001	
	Variance	0,000025	1,397E-06	0,0000	

Average Duration of regimes (Days)	
pz11	135,83
pz22	147,07
ps11	0,32
ps22	209,16

Testing the Markov Model	In Sample	Out of Sample
(Fund & Tech)		
MAE	1,0016	1,0005
MSE	0,9999	0,9997
% Right	0,5362	0,5290
(Tech)		
MAE		1,0003
MSE		0,9996
% Right		0,5439
(Fund)		
MAE		0,9999
MSE		0,9987
% Right		0,5390


Explained Currency AUD
0.05
0
-0.05
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Conditional Std
x 10^-3
6
5
4
Smoothed States Probabilities Chain Z
p(Zt=1)
1
0.5
0
Time
Smoothed States Probabilities Chain S
p(St=1)
Time

NZD/USD

ESTIMATED PARAMETERS

	Starting Value	Lower Bound	Upper Bound	Estimation	Standard Error	P-value
sigma0	0,000052	0,00E+00	0,00090	0,000031	0,000002	0,0000
sigma1	0,000026	0,00E+00	0,00090	0,000042	0,000005	0,0000
Lambda0	0,000000	-0,02964	0,02628	0,001136	0,000198	0,0000
Lambda1	-0,000416	-0,02964	0,02628	-0,001243	0,000450	0,0058
Lambda2	0,000416	-0,02964	0,02628	-0,020700	0,003393	0,0000
pz11	0,900000	0	1	0,977768	0,008535	0,0000
pz22	0,950000	0	1	0,983592	0,006464	0,0000
ps11	0,900000	0	1	0,118332	0,146624	0,4197
ps22	0,950000	0	1	0,992359	0,004256	0,0000

Transiton Matrix For Z		**Transiton Matrix For S**	
0,9778	0,0164	0,1183	0,0076
0,0222	0,9836	0,8817	0,9924

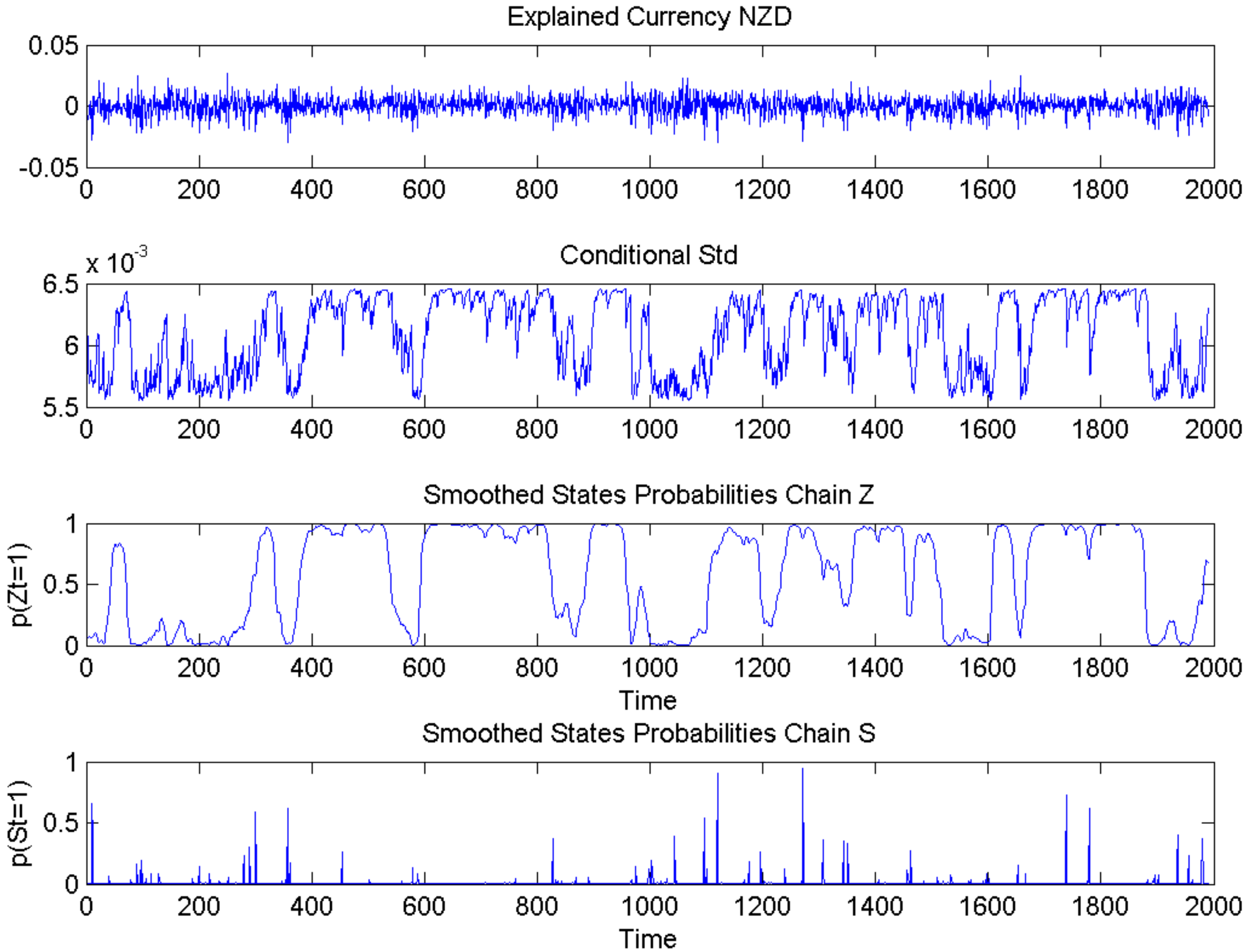
	Long term average	**Threshold**
p(z=1)	0,4246	0,5000
p(s=1)	0,0086	0,5000

ESTIMATED MODEL

		Value	Standard Error	P-Value	State Label
State 1	*Deviation*	-0,020806	0,0034281	0,0000	
	Variance	0,000073	5,567E-06	0,0000	
State 2	*Deviation*	-0,000107	0,0004914	0,8284	
	Variance	0,000073	5,567E-06	0,0000	
State 3	*Deviation*	-0,019564	0,0033985	0,0000	
	Variance	0,000031	1,935E-06	0,0000	
State 4	*Deviation*	0,001136	0,000198	0,0000	
	Variance	0,000031	1,935E-06	0,0000	

Average Duration of regimes (Days)	
pz11	43,98
pz22	59,95
ps11	0,13
ps22	129,87

Testing the Markov Model	In Sample	Out of Sample
(Fund & Tech)		
MAE	1,0015	0,9995
MSE	0,9992	1,0003
% Right	0,5327	0,5091
(Tech)		
MAE		1,0001
MSE		1,0013
% Right		0,5008
(Fund)		
MAE		0,9995
MSE		0,9996
% Right		0,5191


Explained Currency NZD
0.05
0
-0.05
0 200 400 600 800 1000 1200 1400 1600 1800 2000
Conditional Std
x 10-3
6.5
6
5.5
0 200 400 600 800 1000 1200 1400 1600 1800 2000
Smoothed States Probabilities Chain Z
p(Zt=1)
1
0.5
0
0 200 400 600 800 1000 1200 1400 1600 1800 2000
Time
Smoothed States Probabilities Chain S
p(St=1)
1
0.5
0
0 200 400 600 800 1000 1200 1400 1600 1800 2000
Time

NOK/USD

ESTIMATED PARAMETERS

	Starting Value	Lower Bound	Upper Bound	Estimation	Standard Error	P-value
sigma0	0,000021	0,00E+00	0,00065	0,000020	0,000002	0,0000
sigma1	0,000042	0,00E+00	0,00065	0,000023	0,000003	0,0000
Lambda0	0,000000	-0,02522	0,02220	0,000929	0,000295	0,0017
Lambda1	0,000306	-0,02522	0,02220	-0,000369	0,000349	0,2909
Lambda2	0,000153	-0,02522	0,02220	-0,013023	0,002800	0,0000
pz11	0,900000	0	1	0,996134	0,002627	0,0000
pz22	0,900000	0	1	0,985545	0,008918	0,0000
ps11	0,950000	0	1	0,114725	0,110535	0,2995
ps22	0,950000	0	1	0,976895	0,013970	0,0000

Transiton Matrix For Z		Transiton Matrix For S	
0,9961	0,0145	0,1147	0,0231
0,0039	0,9855	0,8853	0,9769

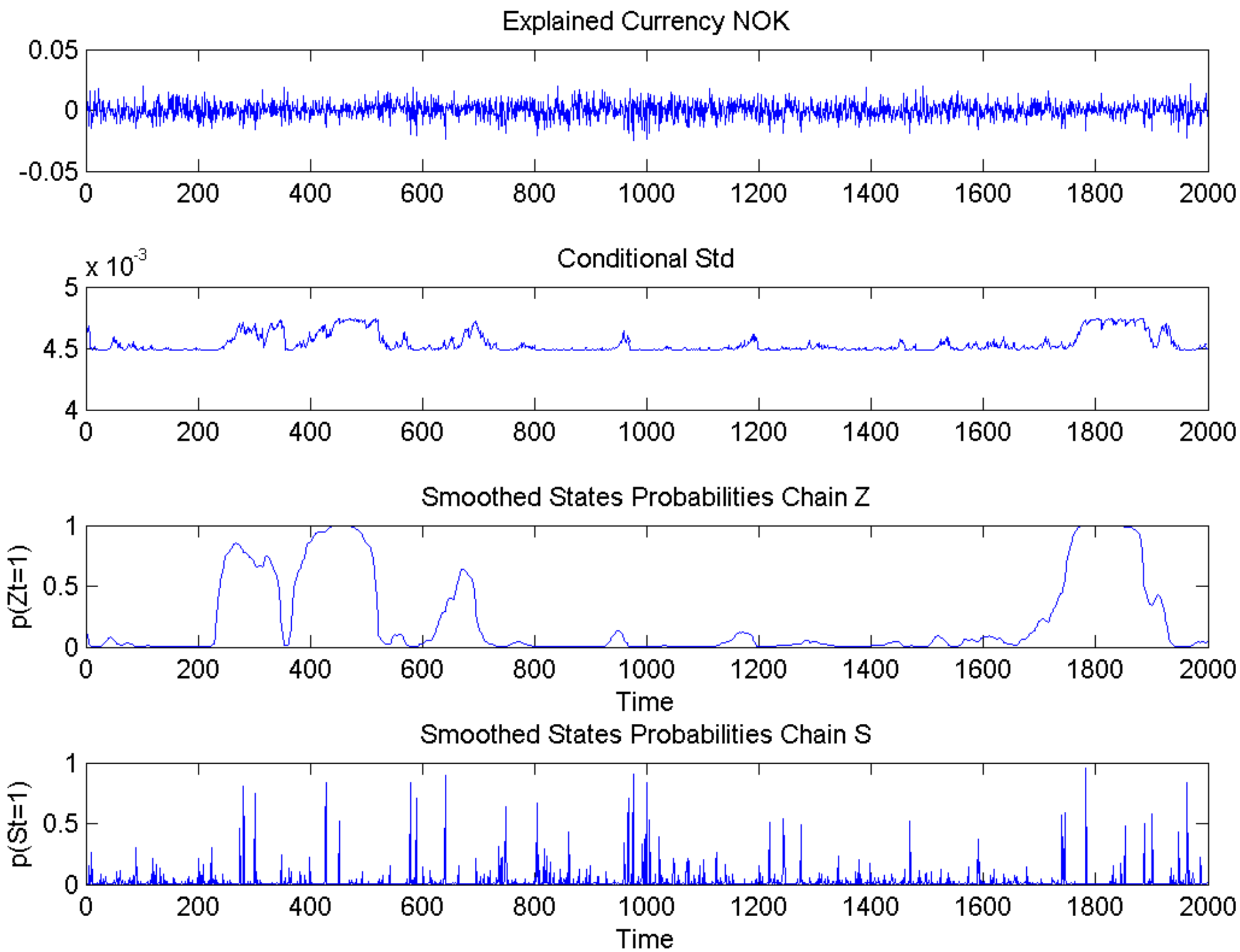
	Long term average	Threshold
p(z=1)	0,7890	0,5000
p(s=1)	0,0254	0,5000

ESTIMATED MODEL

		Value	Standard Error	P-Value	State Label
State 1	*Deviation*	-0,012462	0,0028366	0,0000	
	Variance	0,000043	3,688E-06	0,0000	
State 2	*Deviation*	0,000561	0,0004569	0,2200	
	Variance	0,000043	3,688E-06	0,0000	
State 3	*Deviation*	-0,012094	0,0028151	0,0000	
	Variance	0,000020	2,396E-06	0,0000	
State 4	*Deviation*	0,000929	0,000295	0,0017	
	Variance	0,000020	2,396E-06	0,0000	

Average Duration of regimes (Days)	
pz11	257,65
pz22	68,18
ps11	0,13
ps22	42,28

Testing the Markov Model	In Sample	Out of Sample
(Fund & Tech)		
MAE	0,9989	0,9981
MSE	0,9989	0,9977
% Right	0,5240	0,5556
(Tech)		
MAE		0,9993
MSE		0,9996
% Right		0,5025
(Fund)		
MAE		0,9981
MSE		0,9977
% Right		0,5473



Explained Currency NOK
0.05
0
-0.05
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Conditional Std
x 10^-3
5
4.5
4
Smoothed States Probabilities Chain Z
p(Zt=1)
1
0.5
0
Time
Smoothed States Probabilities Chain S
p(St=1)
Time

Appendix 8

This table summarizes the tests and test statistics for the Logit model fit and specification.

Smoothed Probabilities

		EUR/USD	JPY/USD	GBP/USD	CHF/USD	CAD/USD	AUD/USD	NZD/USD	NOK/USD
Fund & Tech	z	1 908,96	1 936,16	1 239,94	2 493,47	2 430,68	2 415,43	2 246,23	1 877,75
	s	477,87	1 121,56	281,18	1 685,48	13,93	85,95	78,76	228,18
Tech	z	1 911,47	1 944,56	1 547,26	2 495,89	2 479,47	2 455,66	2 285,71	1 974,82
	s	481,94	1 128,14	287,76	1 686,15	16,07	93,04	82,86	229,66
Fund	z	1 927,54	1 984,91	1 264,50	2 504,30	2 439,98	2 456,12	2 397,64	1 880,23
	s	481,97	1 135,02	282,80	1 699,83	14,95	96,31	86,97	235,59

Filtered Probabilities

		EUR/USD	JPY/USD	GBP/USD	CHF/USD	CAD/USD	AUD/USD	NZD/USD	NOK/USD
Fund & Tech	z	1 917,76	2 017,10	1 067,80	2 432,40	2 407,38	2 468,63	2 193,92	1 608,88
	s	471,06	1 135,99	221,90	1 696,66	2,77	65,02	73,27	206,43
Tech	z	1 919,65	2 019,81	1 267,78	2 432,83	2 508,78	2 486,39	2 235,90	1 738,69
	s	474,09	1 141,92	231,18	1 697,45	11,63	73,84	77,25	207,56
Fund	z	1 930,39	2 045,13	1 130,84	2 445,23	2 415,20	2 507,31	2 381,85	1 631,99
	s	475,87	1 149,02	228,31	1 712,22	2,77	73,59	76,23	218,95

Chi-square and Davidson-MacKinnon test (p-values)

Chain	Tested models	EUR/USD	JPY/USD	GBP/USD	CHF/USD	CAD/USD	AUD/USD	NZD/USD	NOK/USD
Z	Comb vs. Techn	0,285	0,002	0,000	0,304	0,000	0,000	0,000	0,000
	Comb vs Fund	0,000	0,000	0,000	0,001	0,005	0,000	0,000	0,547
D-M test	Fund vs. Techn	0,120	0,010	0,000	0,121	0,000	0,000	0,000	0,000
S	Comb vs. Techn	0,087	0,010	0,011	0,854	0,368	0,007	0,085	0,567
	Comb vs Fund	0,223	0,000	0,778	0,000	0,915	0,002	0,012	0,022
D-M test	Fund vs. Techn	0,049	0,010	0,017	0,441	0,375	0,111	0,026	0,228
	Result Z	Comb. or tech	Combined	Combined	Comb. or tech	Combined	Combined	Combined	Comb. or Fund.
	Result S	Inconclusive	Combined	Combined	Comb. Or Tech	Inconclusive	Combined	Combined or Tech	Comb. or Techn

Appendix 9

Appendix 9 presents the regression results from the Logit model with marked significant variable estimates.

For Chain Z

	EUR	*JPY*	*GBP*	*CHF*	*CAD*	*AUD*	*NZD*	*NOK*
Combined								
Constant	1,113***	1,332***	1,955***	-0,20***	0,273	-0,10***	-0,17***	1,229***
GDP	-0,23	-0,09	-4,87***	0,053	-0,87***	0,513***	0,246	-2,08***
NFP	-0,05	0,311	-0,96	-0,45	0,327***	2,135	2,542***	-0,12
ISM	0,030	-0,06	-0,10*	-0,01	-0,00***	-0,05***	0,034***	-0,11***
CC	-0,00	-0,01	-0,10	-0,00	0,053***	0,008***	0,003***	0,014
RSI buy	0,177	-0,70	0,081	-0,01	0,172	-0,53***	-1,24***	-0,02
RSI Sell	0,064	0,377	1,493	-0,16	-0,15***	0,828***	1,108***	0,117
MACD Buy	0,503	-0,13***	0,088	0,436	-0,00	-0,30	-0,33	-0,11
MACD Sell	0,559	-0,16***	0,034	-0,42*	0,000	-0,17	-0,01	-0,27
Stochastic buy	0,374	-0,48	0,392***	0,143	-0,32	-0,09	0,192	0,105
Stochastic sell	0,819***	0,167	-0,01	-0,35	0,235	0,225*	-0,31	0,229
Technical Vars								
Constant	1,134***	1,307***	1,637***	-0,19***	0,291	-0,21***	-0,26***	1,191***
RSI buy	0,149	-0,70	-0,20***	-0,00	0,163	-0,50***	-1,24***	-0,15
RSI Sell	0,043	0,372	1,319	-0,15	-0,10***	0,929***	1,153***	0,357
MACD Buy	0,495	-0,14***	0,016	0,426	-0,01	-0,28	-0,31	-0,08
MACD Sell	0,558	-0,16***	-0,03	-0,42*	0,005	-0,14	0,016	-0,23
Stochastic buy	0,386	-0,47	0,552***	0,138	-0,35*	-0,09	0,228	0,114
Stochastic sell	0,819***	0,138	0,035	-0,35	0,196	0,211	-0,29	0,196
Fundamental Vars								
Constant	1,243***	1,202***	2,074***	-0,23***	0,289	-0,14***	-0,36***	1,236***
GDP	-0,18	0,106	-4,86***	0,031	-0,82***	0,442***	0,087*	-2,09***
NFP	-0,10	0,005	-1,08	-0,43	0,273*	2,394	2,662***	-0,10
ISM	0,029	-0,08	-0,10***	-0,01	-0,00***	-0,04***	0,031***	-0,11***
CC	-0,00	-0,00	-0,10	-0,00	0,054***	0,004***	0,003***	0,015

*** Significant at 1%

*   Significant at 10%

For Chain S

	EUR	JPY	GBP	CHF	CAD	AUD	NZD	NOK
Combined								
Constant	-3,40***	-2,14***	-4,13***	-1,51***	-8,69***	-6,05***	-5,73***	-4,27***
GDP	-0,38	-0,31*	0,721	-0,08***	-0,46*	-1,59	0,247	-0,69
NFP	0,468	1,365	1,561	-0,33*	-9,09	-3,06	4,850	-0,39
ISM	0,056	0,012***	0,151	-0,00	-0,78	-0,16	0,220	0,085
CC	-0,04	-0,01	0,046	-0,00	0,118	0,155	0,045	-0,01
RSI buy	-0,40	-0,01	-0,22	0,152	-85,4	-87,3	-89,6	-1,65
RSI Sell	-1,07	-0,88	-1,11	-0,72***	-85,1	1,869	1,379***	-0,95
MACD Buy	-0,02	-0,04	-0,10	0,120	-89,2	-92,3	1,349***	0,698
MACD Sell	-0,75	0,450	-0,08	0,194	-82,2	-82,1	-76,5	-98,2
Stochastic buy	0,126	-0,35	0,213	-0,45	-63,0***	0,121	-98,0	0,013
Stochastic sell	0,256	-0,52	0,139	-0,08	-57,2	-51,3	-50,2	0,278
Technical Vars								
Constant	-3,34***	-2,15***	-4,07***	-1,50***	-7,03***	-5,45***	-5,59***	-4,16***
RSI buy	-0,50	0,058	-0,13	0,148	-85,5	-87,4	-89,6	-1,81*
RSI Sell	-1,07	-0,95	-1,15	-0,73***	-85,1	1,683	1,661***	-0,93
MACD Buy	-0,05	-0,05	-0,04	0,114	-89,0	-92,4	1,435***	0,684
MACD Sell	-0,73	0,458	-0,07	0,194	-82,2	-82,2	-76,5	-98,2
Stochastic buy	0,167	-0,34	0,162	-0,45	-63,1***	0,083	-98,2	-0,00
Stochastic sell	0,251	-0,57	0,092	-0,08	-56,9	-50,9	-50,1	0,323
Fundamental Vars								
Constant	-3,54***	-2,24***	-4,22***	-1,56***	-9,04***	-5,91***	-5,77***	-4,52***
GDP	-0,50	-0,47	0,674	-0,09***	-0,67***	-1,79	0,029	-0,88
NFP	0,513	1,526	1,730	-0,42	-8,31	-1,21	5,347	-0,36
ISM	0,066	0,017***	0,147	0,001	-0,69	-0,15	0,226	0,109
CC	-0,04	-0,01	0,047	0,001	0,143*	0,137	0,044	-0,02

*** Significant at 1%

*   Significant at 10%

Appendix 10

USING FUNDALMENTALS ONLY 1(3)

EUR	Loose			Strict
# Long trades	0	0	0	0
# Short trades	0	0	0	0
# Closes	1	1	1	1
Avg time Long	0,00	0,00	0,00	0,00
Avg time Short	0,00	0,00	0,00	0,00
Avg time Out	603,00	603,00	603,00	603,00
Profit from Long	0,00	0,00	0,00	0,00
Profit from Short	0,00	0,00	0,00	0,00
Total payoff	0,00	0,00	0,00	0,00

Chain: Z	Beta	P-value	Chain: S	Beta	P-value
Constant	1,2432	0,0000	Constant	-3,5440	0,0000
GDP	-0,1888	0,3746	GDP	-0,5091	0,3064
NFP	-0,1075	0,8144	NFP	0,5137	0,6454
ISM	0,0293	0,3013	ISM	0,0667	0,3133
CC	-0,0060	0,6013	CC	-0,0456	0,1130

JPY	Loose			Strict
# Long trades	24	19	6	0
# Short trades	25	13	10	10
# Closes	45	33	17	11
Avg time Long	4,00	3,58	3,83	0,00
Avg time Short	4,40	4,31	1,40	1,30
Avg time Out	8,82	14,52	33,29	53,64
Profit from Long	-0,04	0,03	0,02	0,00
Profit from Short	-0,07	-0,02	-0,03	-0,02
Total payoff	-0,11	0,00	-0,01	-0,02

Chain: Z	Beta	P-value	Chain: S	Beta	P-value
Constant	1,2432	0,0000	Constant	-2,2488	0,0000
GDP	-0,1888	0,6082	GDP	-0,4711	0,3064
NFP	-0,1075	0,9911	NFP	1,5269	0,6454
ISM	0,0293	0,0014	ISM	0,0173	0,3133
CC	-0,0060	0,8210	CC	-0,0122	0,1130

GBP	Loose			Strict
# Long trades	2	2	2	2
# Short trades	2	0	0	0
# Closes	5	3	3	3
Avg time Long	55,00	46,50	27,00	16,50
Avg time Short	17,00	0,00	0,00	0,00
Avg time Out	91,80	170,00	183,00	190,00
Profit from Long	0,01	0,04	0,00	0,02
Profit from Short	-0,02	0,00	0,00	0,00
Total payoff	-0,01	0,04	0,00	0,02

Chain: Z	Beta	P-value	Chain: S	Beta	P-value
Constant	2,0742	0,0000	Constant	-4,2284	0,0000
GDP	-4,8646	0,0000	GDP	0,6740	0,3988
NFP	-1,0830	0,0517	NFP	1,7308	0,2514
ISM	-0,1047	0,0026	ISM	0,1473	0,0842
CC	-0,1040	0,0000	CC	0,0472	0,2188

USING FUNDALMENTALS ONLY					2(3)

CHF	Loose			Strict
# Long trades	0	0	0	0
# Short trades	0	0	0	0
# Closes	1	1	1	1
Avg time Long	0,00	0,00	0,00	0,00
Avg time Short	0,00	0,00	0,00	0,00
Avg time Out	603,00	603,00	603,00	603,00
Profit from Long	0,00	0,00	0,00	0,00
Profit from Short	0,00	0,00	0,00	0,00
Total payoff	0,00	0,00	0,00	0,00

Chain: Z	Beta	P-value	Chain: S	Beta	P-value
Constant	-0,2383	0,0000	Constant	-1,5606	0,0000
GDP	0,0313	0,8589	GDP	-0,0963	0,6715
NFP	-0,4341	0,2570	NFP	-0,4298	0,3903
ISM	-0,0159	0,4993	ISM	0,0015	0,9617
CC	-0,0061	0,5268	CC	0,0015	0,9071

CAD	Loose			Strict
# Long trades	0	0	0	0
# Short trades	0	0	0	0
# Closes	1	1	1	1
Avg time Long	0,00	0,00	0,00	0,00
Avg time Short	0,00	0,00	0,00	0,00
Avg time Out	603,00	603,00	603,00	603,00
Profit from Long	0,00	0,00	0,00	0,00
Profit from Short	0,00	0,00	0,00	0,00
Total payoff	0,00	0,00	0,00	0,00

Chain: Z	Beta	P-value	Chain: S	Beta	P-value
Constant	0,2900	0,0000	Constant	-9,0433	0,0001
GDP	-0,8277	0,0000	GDP	-0,6718	0,8300
NFP	0,2731	0,4814	NFP	-8,3103	0,3676
ISM	-0,0056	0,8137	ISM	-0,6975	0,3639
CC	0,0546	0,0000	CC	0,1437	0,5457

AUD	Loose			Strict
# Long trades	6	4	1	0
# Short trades	9	5	2	2
# Closes	15	10	4	3
Avg time Long	14,50	10,50	2,00	0,00
Avg time Short	17,22	13,40	16,50	13,00
Avg time Out	24,07	49,40	142,00	192,33
Profit from Long	0,12	0,02	-0,01	0,00
Profit from Short	0,15	0,22	0,18	0,13
Total payoff	0,27	0,24	0,17	0,13

Chain: Z	Beta	P-value	Chain: S	Beta	P-value
Constant	-0,1486	0,0030	Constant	-5,9152	0,0000
GDP	0,4426	0,0149	GDP	-1,7978	0,0874
NFP	2,3941	0,0000	NFP	-1,2167	0,7037
ISM	-0,0457	0,0560	ISM	-0,1529	0,4354
CC	0,0044	0,6518	CC	0,1372	0,0796

USING FUNDALMENTALS ONLY 3(3)

NZD	Loose			Strict
# Long trades	22	15	4	0
# Short trades	23	13	10	0
# Closes	44	29	15	1
Avg time Long	2,23	2,33	2,50	0,00
Avg time Short	9,09	7,23	4,80	0,00
Avg time Out	7,84	16,34	36,33	603,00
Profit from Long	-0,02	0,00	0,01	0,00
Profit from Short	-0,01	0,05	-0,01	0,00
Total payoff	-0,03	0,05	0,00	0,00

Chain: Z	Beta	P-value	Chain: S	Beta	P-value
Constant	-0,3609	0,0000	Constant	-5,7717	0,0000
GDP	0,0875	0,6336	GDP	0,0294	0,9846
NFP	2,6630	0,0000	NFP	5,3475	0,0806
ISM	0,0316	0,1885	ISM	0,2265	0,1684
CC	0,0038	0,6956	CC	0,0448	0,5508

NOK	Loose			Strict
# Long trades	3,00	2,00	1,00	1,00
# Short trades	3,00	3,00	0,00	0,00
# Closes	6,00	5,00	2,00	2,00
Avg time Long	48,33	53,50	44,00	43,00
Avg time Short	52,67	15,33	0,00	0,00
Avg time Out	50,00	90,00	279,50	280,00
Profit from Long	0,20	0,12	0,05	0,04
Profit from Short	0,28	0,16	0,00	0,00
Total payoff	0,48	0,27	0,05	0,04

Chain: Z	Beta	P-value	Chain: S	Beta	P-value
Constant	1,2366	0,0000	Constant	-4,5291	0,0000
GDP	-2,0926	0,0000	GDP	-0,8889	0,2264
NFP	-0,1064	0,8142	NFP	-0,3614	0,8359
ISM	-0,1190	0,0000	ISM	0,1097	0,2744
CC	0,0150	0,1959	CC	-0,0296	0,5172

USING TECHNICALS ONLY 1(3)

EUR	Loose			Strict
# Long trades	25	25	25	25
# Short trades	0	0	0	0
# Closes	26	26	26	26
Avg time Long	1,00	1,00	1,00	1,00
Avg time Short	0,00	0,00	0,00	0,00
Avg time Out	22,23	22,23	22,23	22,23
Profit from Long	-0,01	-0,01	-0,01	-0,01
Profit from Short	0,00	0,00	0,00	0,00
Total payoff	-0,01	-0,01	-0,01	-0,01

Chain: Z	Beta	P-value
Constant	1,1347	0,0000
RSI buy	0,1497	0,3292
RSI Sell	0,0438	0,8366
MACD Buy	0,4957	0,1574
MACD Sell	0,5587	0,1277
Stochastic Buy	0,3865	0,2355
Stochastic Sell	0,8192	0,0059

Chain: S	Beta	P-value
Constant	-3,3401	0,0000
RSI buy	-0,5087	0,2118
RSI Sell	-1,0731	0,1545
MACD Buy	-0,0539	0,9417
MACD Sell	-0,7396	0,4680
Stochastic Buy	0,1674	0,8263
Stochastic Sell	0,2513	0,6501

JPY	Loose			Strict
# Long trades	24	24	24	0
# Short trades	16	17	17	0
# Closes	41	42	42	1
Avg time Long	3,46	3,46	3,46	0,00
Avg time Short	3,63	1,00	1,00	0,00
Avg time Out	11,27	11,98	11,98	603,00
Profit from Long	-0,04	-0,04	-0,04	0,00
Profit from Short	-0,03	-0,06	-0,06	0,00
Total payoff	-0,07	-0,10	-0,10	0,00

Chain: Z	Beta	P-value
Constant	1,3075	0,0000
RSI buy	-0,7067	0,0000
RSI Sell	0,3725	0,0637
MACD Buy	-0,1453	0,6229
MACD Sell	-0,1690	0,5599
Stochastic Buy	-0,4723	0,0235
Stochastic Sell	0,1381	0,6369

Chain: S	Beta	P-value
Constant	-2,1571	0,0000
RSI buy	0,0589	0,2118
RSI Sell	-0,9585	0,1545
MACD Buy	-0,0525	0,9417
MACD Sell	0,4581	0,4680
Stochastic Buy	-0,3456	0,8263
Stochastic Sell	-0,5766	0,6501

GBP	Loose			Strict
# Long trades	0	0	0	0
# Short trades	18	18	18	18
# Closes	19	19	19	19
Avg time Long	0,00	0,00	0,00	0,00
Avg time Short	5,67	5,67	5,67	5,67
Avg time Out	26,37	26,37	26,37	26,37
Profit from Long	0,00	0,00	0,00	0,00
Profit from Short	0,10	0,10	0,10	0,10
Total payoff	0,10	0,10	0,10	0,10

Chain: Z	Beta	P-value
Constant	1,6371	0,0000
RSI buy	-0,2011	0,2261
RSI Sell	1,3194	0,0005
MACD Buy	0,0169	0,9617
MACD Sell	-0,0368	0,9135
Stochastic Buy	0,5524	0,2509
Stochastic Sell	0,0355	0,8925

Chain: S	Beta	P-value
Constant	-4,0731	0,0000
RSI buy	-0,1357	0,7965
RSI Sell	-1,1548	0,2751
MACD Buy	-0,0456	0,9647
MACD Sell	-0,0711	0,9450
Stochastic Buy	0,1626	0,8785
Stochastic Sell	0,0925	0,9056

USING TECHNICALS ONLY 2(3)

CHF	Loose			Strict
# Long trades	44	2	2	0
# Short trades	16	16	17	17
# Closes	59	19	20	18
Avg time Long	1,02	1,00	1,00	0,00
Avg time Short	4,44	4,44	4,12	4,12
Avg time Out	8,25	27,89	26,55	29,61
Profit from Long	0,05	0,01	0,01	0,00
Profit from Short	0,07	0,07	0,07	0,07
Total payoff	0,12	0,08	0,08	0,07

Chain: Z	Beta	P-value
Constant	-0,1963	0,0007
RSI buy	-0,0069	0,9597
RSI Sell	-0,1574	0,3545
MACD Buy	0,4262	0,0843
MACD Sell	-0,4266	0,0975
Stochastic Buy	0,1385	0,5789
Stochastic Sell	-0,3556	0,0914

Chain: S	Beta	P-value
Constant	-1,5034	0,0000
RSI buy	0,1489	0,3800
RSI Sell	-0,7301	0,0091
MACD Buy	0,1142	0,7187
MACD Sell	0,1949	0,5145
Stochastic Buy	-0,4518	0,2787
Stochastic Sell	-0,0833	0,7502

CAD	Loose			Strict
# Long trades	0	0	0	0
# Short trades	0	0	0	0
# Closes	1	1	1	1
Avg time Long	0,00	0,00	0,00	0,00
Avg time Short	0,00	0,00	0,00	0,00
Avg time Out	603,00	603,00	603,00	603,00
Profit from Long	0,00	0,00	0,00	0,00
Profit from Short	0,00	0,00	0,00	0,00
Total payoff	0,00	0,00	0,00	0,00

Chain: Z	Beta	P-value
Constant	0,2918	0,0000
RSI buy	0,1634	0,2341
RSI Sell	-0,1078	0,5317
MACD Buy	-0,0197	0,9370
MACD Sell	0,0055	0,9824
Stochastic Buy	-0,3542	0,1319
Stochastic Sell	0,1970	0,3037

Chain: S	Beta	P-value
Constant	-7,0361	0,0000
RSI buy	-85,5108	1,0000
RSI Sell	-85,1375	1,0000
MACD Buy	-89,0748	1,0000
MACD Sell	-82,2388	1,0000
Stochastic Buy	-63,1438	1,0000
Stochastic Sell	-56,9809	1,0000

AUD	Loose			Strict
# Long trades	0	0	0	0
# Short trades	10	10	10	10
# Closes	11	11	11	11
Avg time Long	0,00	0,00	0,00	0,00
Avg time Short	5,90	5,90	5,90	5,90
Avg time Out	49,45	49,45	49,45	49,45
Profit from Long	0,00	0,00	0,00	0,00
Profit from Short	0,03	0,03	0,03	0,03
Total payoff	0,03	0,03	0,03	0,03

Chain: Z	Beta	P-value
Constant	-0,2162	0,0002
RSI buy	-0,5084	0,0002
RSI Sell	0,9293	0,0000
MACD Buy	-0,2895	0,2475
MACD Sell	-0,1413	0,5683
Stochastic Buy	-0,0926	0,7196
Stochastic Sell	0,2111	0,2687

Chain: S	Beta	P-value
Constant	-5,4511	0,0000
RSI buy	-87,4319	1,0000
RSI Sell	1,6831	0,0328
MACD Buy	-92,4783	1,0000
MACD Sell	-82,2481	1,0000
Stochastic Buy	0,0836	0,9424
Stochastic Sell	-50,9746	1,0000

USING TECHNICALS ONLY				3(3)

NZD	Loose			Strict
# Long trades	27	0	0	0
# Short trades	17	17	17	17
# Closes	45	18	18	18
Avg time Long	2,59	0,00	0,00	0,00
Avg time Short	4,06	4,06	4,06	4,06
Avg time Out	10,31	29,67	29,67	29,67
Profit from Long	0,02	0,00	0,00	0,00
Profit from Short	-0,05	-0,05	-0,05	-0,05
Total payoff	-0,02	-0,05	-0,05	-0,05

Chain: Z	Beta	P-value
Constant	-0,2640	0,0000
RSI buy	-1,2413	0,0000
RSI Sell	1,1531	0,0000
MACD Buy	-0,3151	0,2271
MACD Sell	0,0164	0,9503
Stochastic Buy	0,2285	0,4542
Stochastic Sell	-0,2930	0,2057

Chain: S	Beta	P-value
Constant	-5,5928	0,0000
RSI buy	-89,6860	1,0000
RSI Sell	1,6618	0,0509
MACD Buy	1,4357	0,1922
MACD Sell	-76,5446	1,0000
Stochastic Buy	-98,2602	1,0000
Stochastic Sell	-50,1381	1,0000

SEK	Loose	Strict
# Long trades		
# Short trades		
# Closes		
Avg time Long		
Avg time Short		
Avg time Out		
Profit from Long		
Profit from Short		
Total payoff		

Chain: Z	Beta	P-value
Constant		
RSI buy		
RSI Sell		
MACD Buy		
MACD Sell		
Stochastic Buy		
Stochastic Sell		

Chain: S	Beta	P-value
Constant		
RSI buy		
RSI Sell		
MACD Buy		
MACD Sell		
Stochastic Buy		
Stochastic Sell		

NOK	Loose			Strict
# Long trades	16	16	16	0
# Short trades	0	0	0	0
# Closes	17	17	17	1
Avg time Long	4,44	4,44	4,44	0,00
Avg time Short	0,00	0,00	0,00	0,00
Avg time Out	31,29	31,29	31,29	603,00
Profit from Long	-0,09	-0,09	-0,09	0,00
Profit from Short	0,00	0,00	0,00	0,00
Total payoff	-0,09	-0,09	-0,09	0,00

Chain: Z	Beta	P-value
Constant	1,1917	0,0000
RSI buy	-0,1534	0,2867
RSI Sell	0,3574	0,1156
MACD Buy	-0,0891	0,7427
MACD Sell	-0,2365	0,3696
Stochastic Buy	0,1149	0,6998
Stochastic Sell	0,1967	0,4060

Chain: S	Beta	P-value
Constant	-4,1631	0,0000
RSI buy	-1,8158	0,0872
RSI Sell	-0,9334	0,3766
MACD Buy	0,6841	0,3652
MACD Sell	-98,2891	1,0000
Stochastic Buy	-0,0076	0,9943
Stochastic Sell	0,3231	0,7624

USING BOTH TECHNICALS AND FUNDAMENTALS

EUR	Loose			Strict
# Long trades	25	25	25	25
# Short trades	0	0	0	0
# Closes	26	26	26	26
Avg time Long	1,00	1,00	1,00	1,00
Avg time Short	0,00	0,00	0,00	0,00
Avg time Out	22,23	22,23	22,23	22,23
Profit from Long	-0,01	-0,01	-0,01	-0,01
Profit from Short	0,00	0,00	0,00	0,00
Total payoff	-0,01	-0,01	-0,01	-0,01

Chain: Z	Beta	P-value
Constant	1,1135	0,0000
GDP	-0,2353	0,2767
NFP	-0,0527	0,9092
ISM	0,0305	0,2868
CC	-0,0073	0,5254
RSI buy	0,1773	0,2539
RSI Sell	0,0647	0,7627
MACD Buy	0,5036	0,1513
MACD Sell	0,5595	0,1274
Stochastic Buy	0,3746	0,2515
Stochastic Sell	0,8191	0,0059

Chain: S	Beta	P-value
Constant	-3,4033	0,0000
GDP	-0,3890	0,4336
NFP	0,4683	0,6733
ISM	0,0568	0,3953
CC	-0,0467	0,1059
RSI buy	-0,4043	0,3285
RSI Sell	-1,0711	0,1563
MACD Buy	-0,0284	0,9693
MACD Sell	-0,7535	0,4601
Stochastic Buy	0,1267	0,8683
Stochastic Sell	0,2563	0,6446

JPY	Loose			Strict
# Long trades	4	1	1	0
# Short trades	8	8	6	4
# Closes	10	10	8	5
Avg time Long	18,00	14,00	14,00	0,00
Avg time Short	33,75	22,13	15,50	11,25
Avg time Out	26,10	41,20	62,00	111,60
Profit from Long	-0,08	-0,02	-0,02	0,00
Profit from Short	-0,03	-0,01	0,00	-0,02
Total payoff	-0,11	-0,03	-0,02	-0,02

Chain: Z	Beta	P-value
Constant	1,1135	0,0000
GDP	-0,2353	0,6728
NFP	-0,0527	0,4965
ISM	0,0305	0,0176
CC	-0,0073	0,3231
RSI buy	0,1773	0,0000
RSI Sell	0,0647	0,0643
MACD Buy	0,5036	0,6456
MACD Sell	0,5595	0,5737
Stochastic Buy	0,3746	0,0214
Stochastic Sell	0,8191	0,5678

Chain: S	Beta	P-value
Constant		0,0000
GDP		
NFP		
ISM		
CC		
RSI buy		
RSI Sell		
MACD Buy		
MACD Sell		
Stochastic Buy		
Stochastic Sell		

GBP	Loose			Strict
# Long trades	3	4	4	3
# Short trades	4	0	0	0
# Closes	8	5	5	4
Avg time Long	35,33	20,00	11,25	8,00
Avg time Short	12,50	0,00	0,00	0,00
Avg time Out	55,88	104,60	111,60	144,75
Profit from Long	0,02	0,04	0,00	0,02
Profit from Short	0,03	0,00	0,00	0,00
Total payoff	0,05	0,04	0,00	0,02

Chain: Z	Beta	P-value
Constant	1,9554	0,0000
GDP	-4,8781	0,0000
NFP	-0,9660	0,0848
ISM	-0,1077	0,0027
CC	-0,1054	0,0000
RSI buy	0,0818	0,6671
RSI Sell	1,4937	0,0002
MACD Buy	0,0882	0,8200
MACD Sell	0,0341	0,9277
Stochastic Buy	0,3929	0,4363
Stochastic Sell	-0,0199	0,9463

Chain: S	Beta	P-value
Constant	-4,1364	0,0000
GDP	0,7213	0,3643
NFP	1,5617	0,2984
ISM	0,1515	0,0838
CC	0,0469	0,2239
RSI buy	-0,2239	0,6760
RSI Sell	-1,1119	0,2947
MACD Buy	-0,1039	0,9198
MACD Sell	-0,0807	0,9377
Stochastic Buy	0,2131	0,8414
Stochastic Sell	0,1394	0,8589

USING BOTH TECHNICALS AND FUNDAMENTALS

CHF	Loose			Strict
# Long trades	44	2	2	0
# Short trades	16	16	17	17
# Closes	59	19	20	18
Avg time Long	1,02	1,00	1,00	0,00
Avg time Short	4,44	4,44	4,12	4,12
Avg time Out	8,25	27,89	26,55	29,61
Profit from Long	0,05	0,01	0,01	0,00
Profit from Short	0,07	0,07	0,07	0,07
Total payoff	0,12	0,08	0,08	0,07

Chain: Z	Beta	P-value
Constant	-0,2053	0,0007
GDP	0,0531	0,7653
NFP	-0,4598	0,2323
ISM	-0,0163	0,4899
CC	-0,0066	0,4935
RSI buy	-0,0145	0,9164
RSI Sell	-0,1666	0,3293
MACD Buy	0,4369	0,0773
MACD Sell	-0,4264	0,0977
Stochastic Buy	0,1437	0,5654
Stochastic Sell	-0,3531	0,0938

Chain: S	Beta	P-value
Constant	-1,5197	0,0000
GDP	-0,0889	0,6956
NFP	-0,3399	0,4940
ISM	-0,0041	0,8947
CC	-0,0016	0,9013
RSI buy	0,1523	0,3733
RSI Sell	-0,7251	0,0097
MACD Buy	0,1210	0,7030
MACD Sell	0,1945	0,5155
Stochastic Buy	-0,4539	0,2767
Stochastic Sell	-0,0822	0,7535

CAD	Loose			Strict
# Long trades	0	0	0	0
# Short trades	0	0	0	0
# Closes	1	1	1	1
Avg time Long	0,00	0,00	0,00	0,00
Avg time Short	0,00	0,00	0,00	0,00
Avg time Out	603,00	603,00	603,00	603,00
Profit from Long	0,00	0,00	0,00	0,00
Profit from Short	0,00	0,00	0,00	0,00
Total payoff	0,00	0,00	0,00	0,00

Chain: Z	Beta	P-value
Constant	0,2739	0,0000
GDP	-0,8775	0,0000
NFP	0,3276	0,4012
ISM	-0,0028	0,9072
CC	0,0535	0,0000
RSI buy	0,1730	0,2131
RSI Sell	-0,1563	0,3760
MACD Buy	-0,0065	0,9794
MACD Sell	0,0010	0,9969
Stochastic Buy	-0,3201	0,1785
Stochastic Sell	0,2352	0,2263

Chain: S	Beta	P-value
Constant	-8,6949	0,0004
GDP	-0,4624	0,8794
NFP	-9,0997	0,3549
ISM	-0,7886	0,3389
CC	0,1184	0,6073
RSI buy	-85,4780	1,0000
RSI Sell	-85,1127	1,0000
MACD Buy	-89,2640	1,0000
MACD Sell	-82,2893	1,0000
Stochastic Buy	-63,0753	1,0000
Stochastic Sell	-57,2705	1,0000

AUD	Loose			Strict
# Long trades	13	5	0	0
# Short trades	10	9	6	4
# Closes	24	15	7	5
Avg time Long	3,08	2,20	0,00	0,00
Avg time Short	10,40	5,78	4,67	6,50
Avg time Out	19,13	36,00	82,14	115,40
Profit from Long	-0,01	-0,01	0,00	0,00
Profit from Short	0,12	-0,03	-0,04	-0,02
Total payoff	0,11	-0,04	-0,04	-0,02

Chain: Z	Beta	P-value
Constant	-0,1071	0,0811
GDP	0,5135	0,0051
NFP	2,1354	0,0000
ISM	-0,0510	0,0354
CC	0,0084	0,3919
RSI buy	-0,5342	0,0001
RSI Sell	0,8284	0,0000
MACD Buy	-0,3014	0,2327
MACD Sell	-0,1733	0,4880
Stochastic Buy	-0,0924	0,7220
Stochastic Sell	0,2252	0,2432

Chain: S	Beta	P-value
Constant	-6,0560	0,0000
GDP	-1,5936	0,1292
NFP	-3,0605	0,3697
ISM	-0,1657	0,4059
CC	0,1557	0,0633
RSI buy	-87,3166	1,0000
RSI Sell	1,8697	0,0259
MACD Buy	-92,3308	1,0000
MACD Sell	-82,1166	1,0000
Stochastic Buy	0,1213	0,9180
Stochastic Sell	-51,3276	1,0000

USING BOTH TECHNICALS AND FUNDAMENTALS 3(3)

NZD	Loose			Strict
# Long trades	22	15	4	0
# Short trades	23	13	10	0
# Closes	44	29	15	1
Avg time Long	2,23	2,33	2,50	0,00
Avg time Short	9,09	7,23	4,80	0,00
Avg time Out	7,84	16,34	36,33	603,00
Profit from Long	-0,02	0,00	0,01	0,00
Profit from Short	-0,01	0,05	-0,01	0,00
Total payoff	-0,03	0,05	0,00	0,00

Chain: Z	Beta	P-value
Constant	-0,1785	0,0040
GDP	0,2461	0,2016
NFP	2,5426	0,0000
ISM	0,0343	0,1668
CC	0,0039	0,6979
RSI buy	-1,2477	0,0000
RSI Sell	1,1085	0,0000
MACD Buy	-0,3378	0,1999
MACD Sell	-0,0108	0,9676
Stochastic Buy	0,1924	0,5292
Stochastic Sell	-0,3122	0,1812

Chain: S	Beta	P-value
Constant	-5,7337	0,0000
GDP	0,2475	0,8767
NFP	4,8504	0,1238
ISM	0,2202	0,2093
CC	0,0456	0,5527
RSI buy	-89,6860	1,0000
RSI Sell	1,3795	0,1186
MACD Buy	1,3497	0,2239
MACD Sell	-76,5738	1,0000
Stochastic Buy	-98,0945	1,0000
Stochastic Sell	-50,2550	1,0000

NOK	Loose			Strict
# Long trades	3	2	1	1
# Short trades	3	3	0	0
# Closes	6	5	2	2
Avg time Long	48,33	53,50	44,00	43,00
Avg time Short	52,67	15,33	0,00	0,00
Avg time Out	50,00	90,00	279,50	280,00
Profit from Long	0,20	0,12	0,05	0,04
Profit from Short	0,28	0,16	0,00	0,00
Total payoff	0,48	0,27	0,05	0,04

Chain: Z	Beta	P-value
Constant	1,2294	0,0000
GDP	-2,0817	0,0000
NFP	-0,1222	0,7875
ISM	-0,1188	0,0000
CC	0,0150	0,2014
RSI buy	-0,0257	0,8662
RSI Sell	0,1170	0,6152
MACD Buy	-0,1169	0,6765
MACD Sell	-0,2745	0,3142
Stochastic Buy	0,1054	0,7270
Stochastic Sell	0,2291	0,3483

Chain: S	Beta	P-value
Constant	-4,2792	0,0000
GDP	-0,6946	0,3468
NFP	-0,3928	0,8234
ISM	0,0851	0,4005
CC	-0,0194	0,6701
RSI buy	-1,6564	0,1216
RSI Sell	-0,9506	0,3713
MACD Buy	0,6990	0,3564
MACD Sell	-98,2542	1,0000
Stochastic Buy	0,0140	0,9896
Stochastic Sell	0,2783	0,7949

Appendix 11

This table shows the DuPont analysis for our trading rule.

		Fundamentals				Technicals				Combined			
		Loose			Strict	Loose			Strict	Loose			Strict
	Long Positions / Year	0,00	0,00	0,00	0,00	10,36	10,36	10,36	10,36	10,36	10,36	10,36	10,36
	Return / long trade	0,00%	0,00%	0,00%	0,00%	-0,04%	-0,04%	-0,04%	-0,04%	-0,04%	-0,04%	-0,04%	-0,04%
	% Long	0,00%	0,00%	0,00%	0,00%	4,15%	4,15%	4,15%	4,15%	4,15%	4,15%	4,15%	4,15%
	Short positions / Year	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
EUR	Return / short trade	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
	% Short	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
	Trading Costs	0,00%	0,00%	0,00%	0,00%	1,04%	1,04%	1,04%	1,04%	1,04%	1,04%	1,04%	1,04%
	Net return p.a.	0,00%	0,00%	0,00%	0,00%	-1,45%	-1,45%	-1,45%	-1,45%	-1,45%	-1,45%	-1,45%	-1,45%
	Annualized net return	**0,00%**	**0,00%**	**0,00%**	**0,00%**	**-35,04%**	**-35,04%**	**-35,04%**	**-35,04%**	**-35,04%**	**-35,04%**	**-35,04%**	**-35,04%**
	Long Positions / Year	9,95	7,88	2,49	0,00	9,95	9,95	9,95	0,00	1,66	0,41	0,41	0,00
	Return / long trade	-0,18%	0,14%	0,35%	0,00%	-0,16%	-0,16%	-0,16%	0,00%	-2,03%	-1,51%	-1,51%	0,00%
	% Long	15,92%	11,28%	3,81%	0,00%	13,76%	13,76%	13,76%	0,00%	11,94%	2,32%	2,32%	0,00%
	Short positions / Year	10,36	5,39	4,15	4,15	6,63	7,05	7,05	0,00	3,32	3,32	2,49	1,66
JPY	Return / short trade	-0,27%	-0,18%	-0,28%	-0,18%	-0,16%	-0,33%	-0,33%	0,00%	-0,38%	-0,16%	-0,05%	-0,62%
	% Short	6,93%	4,82%	2,05%	2,16%	3,86%	1,11%	1,11%	0,00%	47,29%	29,55%	15,58%	7,46%
	Trading Costs	2,03%	1,33%	0,66%	0,41%	1,66%	1,70%	1,70%	0,00%	0,50%	0,37%	0,29%	0,17%
	Net return p.a.	-6,71%	-1,19%	-0,94%	-1,17%	-4,38%	-5,69%	-5,69%	0,00%	-5,12%	-1,54%	-1,04%	-1,19%
	Annualized net return	**-29,36%**	**-7,37%**	**-16,01%**	**-54,07%**	**-24,87%**	**-38,26%**	**-38,26%**	**0,00%**	**-8,64%**	**-4,83%**	**-5,80%**	**-1,28%**
	Long Positions / Year	0,83	0,83	0,83	0,83	0,00	0,00	0,00	0,00	1,24	1,66	1,66	1,24
	Return / long trade	0,75%	1,84%	0,05%	0,80%	0,00%	0,00%	0,00%	0,00%	0,63%	1,07%	0,08%	0,60%
	% Long	18,24%	15,42%	8,96%	5,47%	0,00%	0,00%	0,00%	0,00%	17,58%	13,27%	7,46%	3,98%
	Short positions / Year	0,83	0,00	0,00	0,00	7,46	7,46	7,46	7,46	1,66	0,00	0,00	0,00
GBP	Return / short trade	0,00%	0,00%	0,00%	0,00%	0,63%	0,63%	0,59%	0,59%	0,18%	0,00%	0,00%	0,00%
	% Short	5,64%	0,00%	0,00%	0,00%	16,92%	16,92%	16,92%	16,92%	8,29%	0,00%	0,00%	0,00%
	Trading Costs	0,17%	0,08%	0,08%	0,08%	0,75%	0,75%	0,75%	0,75%	0,29%	0,17%	0,17%	0,12%
	Net return p.a.	0,46%	1,44%	-0,04%	0,58%	3,93%	3,93%	3,65%	3,65%	0,79%	1,61%	-0,03%	0,63%
	Annualized net return	**1,91%**	**9,36%**	**-0,44%**	**10,59%**	**23,23%**	**23,23%**	**21,61%**	**21,61%**	**3,07%**	**12,16%**	**-0,44%**	**15,77%**

		Fundamentals				Technicals				Combined			
		Loose			Strict	Loose			Strict	Loose			Strict
CHF	Long Positions / Year	0,00	0,00	0,00	0,00	18,24	0,83	0,83	0,00	18,24	0,83	0,83	0,00
	Return / long trade	0,00%	0,00%	0,00%	0,00%	0,12%	0,62%	0,62%	0,00%	0,12%	0,62%	0,62%	0,00%
	% Long	0,00%	0,00%	0,00%	0,00%	7,46%	0,33%	0,33%	0,00%	7,46%	0,33%	0,33%	0,00%
	Short positions / Year	0,00	0,00	0,00	0,00	6,63	6,63	7,05	7,05	6,63	6,63	7,05	7,05
	Return / short trade	0,00%	0,00%	0,00%	0,00%	0,42%	0,42%	0,41%	0,41%	0,42%	0,42%	0,41%	0,41%
	% Short	0,00%	0,00%	0,00%	0,00%	11,77%	11,77%	11,61%	11,61%	11,77%	11,77%	11,61%	11,61%
	Trading Costs	0,00%	0,00%	0,00%	0,00%	2,49%	0,75%	0,79%	0,70%	2,49%	0,75%	0,79%	0,70%
	Net return p.a.	0,00%	0,00%	0,00%	0,00%	2,46%	2,54%	2,62%	2,19%	2,46%	2,54%	2,62%	2,19%
	Annualized net return	**0,00%**	**0,00%**	**0,00%**	**0,00%**	**12,78%**	**21,01%**	**21,90%**	**18,84%**	**12,78%**	**21,01%**	**21,90%**	**18,84%**
CAD	Long Positions / Year	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Return / long trade	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
	% Long	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
	Short positions / Year	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Return / short trade	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
	% Short	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
	Trading Costs	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
	Net return p.a.	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
	Annualized net return	**0,00%**	**0,00%**	**0,00%**	**0,00%**	**0,00%**	**0,00%**	**0,00%**	**0,00%**	**0,00%**	**0,00%**	**0,00%**	**0,00%**
AUD	Long Positions / Year	2,49	1,66	0,41	0,00	0,00	0,00	0,00	0,00	5,39	2,07	0,00	0,00
	Return / long trade	1,96%	0,45%	-0,99%	0,00%	0,00%	0,00%	0,00%	0,00%	-0,10%	-0,11%	0,00%	0,00%
	% Long	14,43%	6,97%	0,33%	0,00%	0,00%	0,00%	0,00%	0,00%	6,63%	1,82%	0,00%	0,00%
	Short positions / Year	3,73	2,07	0,83	0,83	4,15	4,15	4,15	4,15	4,15	3,73	2,49	1,66
	Return / short trade	1,70%	4,37%	8,91%	6,58%	0,32%	0,32%	0,32%	0,32%	1,22%	-0,34%	-0,68%	-0,56%
	% Short	25,70%	11,11%	5,47%	4,31%	9,78%	9,78%	9,78%	9,78%	17,25%	8,62%	4,64%	4,31%
	Trading Costs	0,62%	0,37%	0,12%	0,08%	0,41%	0,41%	0,41%	0,41%	0,95%	0,58%	0,25%	0,17%
	Net return p.a.	10,59%	9,43%	6,86%	5,37%	0,91%	0,91%	0,91%	0,91%	3,57%	-2,08%	-1,93%	-1,10%
	Annualized net return	**26,38%**	**52,18%**	**118,10%**	**124,64%**	**9,32%**	**9,32%**	**9,32%**	**9,32%**	**14,96%**	**-19,93%**	**-41,62%**	**-25,54%**

		Fundamentals				Technicals				Combined			
		Loose			Strict	Loose			Strict	Loose			Strict
NZD	Long Positions / Year	9,12	6,22	1,66	0,00	11,19	0,00	0,00	0,00	9,12	6,22	1,66	0,00
	Return / long trade	-0,11%	0,02%	0,28%	0,00%	0,09%	0,00%	0,00%	0,00%	-0,11%	0,02%	0,28%	0,00%
	% Long	8,13%	5,80%	1,66%	0,00%	11,61%	0,00%	0,00%	0,00%	8,13%	5,80%	1,66%	0,00%
	Short positions / Year	9,54	5,39	4,15	0,00	7,05	7,05	7,05	7,05	9,54	5,39	4,15	0,00
	Return / short trade	-0,03%	0,38%	-0,14%	0,00%	-0,29%	-0,29%	-0,29%	-0,29%	-0,03%	0,38%	-0,14%	0,00%
	% Short	34,66%	15,59%	7,96%	0,00%	11,44%	11,44%	11,44%	11,44%	34,66%	15,59%	7,96%	0,00%
	Trading Costs	1,87%	1,16%	0,58%	0,00%	1,82%	0,70%	0,70%	0,70%	1,87%	1,16%	0,58%	0,00%
	Net return p.a.	-3,17%	1,03%	-0,70%	0,00%	-2,85%	-2,72%	-2,72%	-2,72%	-3,17%	1,03%	-0,70%	0,00%
	Annualized net return	**-7,40%**	**4,83%**	**-7,32%**	**0,00%**	**-12,38%**	**-23,81%**	**-23,81%**	**-23,81%**	**-7,40%**	**4,83%**	**-7,32%**	**0,00%**
NOK	Long Positions / Year	1,24	0,83	0,41	0,41	6,63	6,63	6,63	0,00	1,24	0,83	0,41	0,41
	Return / long trade	6,68%	5,75%	5,22%	3,71%	-0,59%	-0,59%	-0,59%	0,00%	6,68%	5,75%	5,22%	3,71%
	% Long	24,05%	17,74%	7,30%	7,13%	11,77%	11,77%	11,77%	0,00%	24,05%	17,74%	7,30%	7,13%
	Short positions / Year	1,24	1,24	0,00	0,00	0,00	0,00	0,00	0,00	1,24	1,24	0,00	0,00
	Return / short trade	9,19%	5,20%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	9,19%	5,20%	0,00%	0,00%
	% Short	26,20%	7,63%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	26,20%	7,63%	0,00%	0,00%
	Trading Costs	0,25%	0,21%	0,04%	0,04%	0,66%	0,66%	0,66%	0,00%	0,25%	0,21%	0,04%	0,04%
	Net return p.a.	19,49%	11,03%	2,12%	1,50%	-4,57%	-4,57%	-4,57%	0,00%	19,49%	11,03%	2,12%	1,50%
	Annualized net return	**38,78%**	**43,49%**	**29,10%**	**20,98%**	**-38,81%**	**-38,81%**	**-38,81%**	**0,00%**	**38,78%**	**43,49%**	**29,10%**	**20,98%**
Average	Long Positions / Year	3,38	2,49	0,83	0,18	8,05	3,97	3,97	1,48	6,75	3,20	2,19	1,72
	Return / long trade	1,30%	1,17%	0,70%	0,64%	-0,08%	-0,03%	-0,03%	-0,01%	0,74%	0,83%	0,66%	0,61%
	% Long	11,54%	8,17%	3,15%	1,80%	6,97%	4,29%	4,29%	0,59%	11,42%	6,49%	3,32%	2,18%
	Short positions / Year	3,67	2,01	1,30	0,71	4,56	4,62	4,68	3,67	3,79	2,90	2,31	1,48
	Return / short trade	1,51%	1,40%	1,21%	0,91%	0,13%	0,11%	0,10%	0,15%	1,51%	0,79%	-0,07%	-0,11%
	% Short	14,16%	5,59%	2,21%	0,92%	7,68%	7,29%	7,27%	7,11%	20,78%	10,45%	5,68%	3,34%
	Trading Costs	0,70%	0,45%	0,21%	0,09%	1,26%	0,86%	0,86%	0,52%	1,05%	0,61%	0,45%	0,32%
	Avg net return / Year	**2,95%**	**3,11%**	**1,04%**	**0,90%**	**-0,85%**	**-1,01%**	**-1,04%**	**0,37%**	**2,37%**	**1,59%**	**-0,06%**	**0,08%**
	Avg. annualized net return	**4,33%**	**14,64%**	**17,63%**	**14,59%**	**-9,40%**	**-11,76%**	**-11,87%**	**-1,30%**	**2,64%**	**3,10%**	**-5,60%**	**-0,90%**